Cognitive Bias in Patient-Provider Communication: Sensing and Design to Reduce Health Disparities

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ABSTRACT

Cognitive bias is pervasive in healthcare. It drives differential diagnosis and timely recognition of acute onset illness, but it also contributes to healthcare inequity. Patients may not be treated equitably due to different identities (race, gender, socio-economic status, etc) or different diseases (obesity, diabetes, hypertension, etc). In our work we investigate if biased behaviors between patients and providers can be detected through a technique known as Social Signal Processing. Our project explores how computational sensing can be used to identify behavior biases, and if it can promote improved patient-provider communication, ultimately reducing health disparities for low income, racially diverse patients in primary care. Through a partnership with academic and community-based health systems in Seattle and San Diego, we aim to characterize behavior between providers and patients, develop a behavior sensing tool, design interventional feedback, and evaluate how effective that tool and feedback are at improving patient-provider communication. We believe that this approach will lead to new techniques for shaping the next generation of healthcare providers and educators, helping them better promote healthcare access, quality, and equity.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; *Interaction paradigms*; *Collaborative and social computing*.

KEYWORDS

bias, healthcare, social signal processing, design, health disparities

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INTRODUCTION

Cognitive biases are individual behaviors shaped by subjective perceptions that create their subsequent judgements rather than any sort of reproducible rationality. They were first described by Tversky and Kahneman who found that human differences in decision-making were linked to unique heuristics, or shortcuts, that allowed an individual to take an input and more quickly arrive at a decision. [17] While these heuristic based approaches were much faster, they sometimes led to severe and systemic errors. [34]

Today, we know that these heuristics live on in the form of prejudice and stereotypes, both explicit and implicit, which are pervasive in society. [21] Generally referred to as hidden bias, these decision-making shortcuts are often unconscious, expressed through subtle behavior differences given various situational contexts. Communication behaviors such as talk time, interruptions, and body movement, can be automatically sensed and may reflect any biases present, and generally impact the quality of interaction between two or more people. [4]

Bias in Healthcare

Biased behavior related to patient treatment in the healthcare system often hides within the communication that takes place between patients and their providers. [7] Healthcare bias negatively impacts quality of care and perpetuates disparities such as lack of appropriate treatment and inadequate pain support. [26] These biases are well-documented among healthcare providers, and are known to negatively impact patient-provider interaction, treatment decisions, care quality, and patient outcomes. [20] Black patients, for instance, are prescribed less pain medication, receive fewer cardiovascular referrals, and achieve poorer reproductive outcomes than white patients. [9] Bias shapes the behavior of healthcare providers and leads to subtle differences in medical treatment according to race, ethnicity, gender, and socio-economic status, which perpetuate these disparities in healthcare. [11, 14]

Biases have demonstrable effects in healthcare, and the expertise gap between patients and providers further compounds those effects. Patients, with varying degrees of health literacy, tend to focus on actions, strategies, and personal perspectives to help them live with the health conditions they have. Providers, on the other hand, tend to focus on what they need to know or do so they can 'fix' their patient, emphasizing medical knowledge and facts. [16] This often leads patients to focus on reporting relevant symptoms to their physician and focusing on the problem that is central to their appointment rather than discussing concerns which may be perceived to be peripheral. [18] Patients and providers both need to understand each other's relative expertise so they can create common understanding and be a more collaborative team.

Computationally Sensing Biased Behavior

Leaders in the field have long called for better ways to measure bias in healthcare. As described by Shavers et al., there is a need for "systematic examinations of patient-physician interactions, particularly as they relate to communication styles and nonverbal behaviors that have the potential to elicit the perception of discrimination among diverse patients". [30] Traditionally, research for assessing bias in patient encounters focuses on the use of self-reporting tools like surveys to capture the experience of patients. [31] Surveys provide great insights into subjective experience; but with topics like biased interaction, patients who actively experience inequitable behavior first hand might not perceive the inequity.

The bias some people experience may be so pervasive that they have become accustomed to it. As such a patient might not be able to understand the bias they experience until shown that their experience is not universal.

We propose to move beyond only subjective measurement of experiences to develop automated, objective approaches that could be widely deployed. Social Signal Processing (SSP) is a computational approach to extract communicative features and other behavioral cues that can provide socially contextualized data about human interactions. By detecting and interpreting verbal and nonverbal communication behaviors, SSP can take what is said or how something is said and infer emotional state, understand individual attitudes, or even assess relationships between people. [4]

Our UnBIASED (Understanding Biased patient-provider Interaction And Supporting Enhanced Discourse) project[1] is rooted in human-centered principles and aims to develop and investigate how to bring visibility to hidden healthcare bias. Our goal is to detect discrepancies within patient-provider communication using sensing technology to make biased behavior visible. We believe that SSP promises wide-scale applications in healthcare where patient-centered communication is critical to building rapport, establishing trusted patient-provider relationships, empowering patients, and ultimately promoting health equity for all.

[1] http://unbiased.health

With this position paper we aim to discuss how detection of biases can be accomplished in the complex healthcare environment and how UnBIASED can create targeted interventions with patients and providers to improve interactions in the medical office, limit cognitive bias, and ultimately improve health outcomes.

PRELIMINARY WORK

This work represents a convergence of independent research programs and synergistic efforts pursued at UC San Diego (UCSD) and University of Washington (UW) to develop and implement solutions that mitigate hidden bias in patient-provider communication and address health disparities.

Understanding hidden bias in healthcare

Research at UW has highlighted attitudes and stereotypes related to race, sexual orientation, and weight. [7, 27, 28] It also demonstrated how hidden biases can impact communication between providers and their patients; for instance, some providers were found to hold the stereotype that white patients are more compliant with medical treatment than African American patients [29]; other doctors were less likely to prescribe narcotic pain medication to African American patients than white patients. [26] These works further showcase how verbal dominance on behalf of the provider, use of less patient-centered language, and less patient involvement in decision making, manifest due to

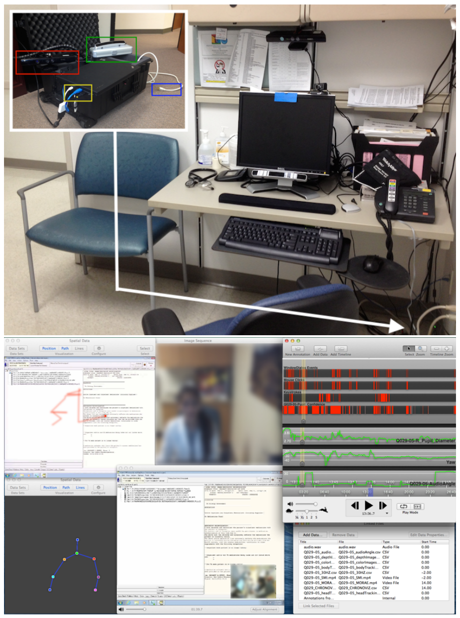

Figure 1: Data capture systems used in clinical spaces to capture audio, video, eye tracking, body tracking, and more [36]

biases and stereotypes, giving us hints at the importance of communication sensing to detect hidden biases. [7]

Sensing patient-provider interactions

Research at UCSD has encompassed both capture and analysis of behaviors in clinical environments; from the analysis of how interpreters influence patient-provider interaction across language barriers [19, 35], to the impact of Electronic Medical Records (EMR) on communication [36], prior work has revealed how unobtrusive sensing technology can help us better understand patient-provider communication. As Fig. 1 shows, we previously used an array of multimodal sensing technology (depth cameras, directional microphones, eye trackers, etc) to collect detailed interaction behavior data in clinics.

Computational analysis of patient-provider interactions has led to much more in-depth and semi-automated assessment of interpersonal communication behavior. [32] Use of computational behavior sensing helped establish the research method "Computational Ethnography" [37] referring to the in-depth automated assessment of interpersonal and communication behavior. This approach enables better understanding of attention (through gaze and eye-tracking [24]), rapport (through verbal turn-taking and conversational dominance [33]), and objective measures of workload during medical consultations. [6] We believe that these approaches will influence not only the way we design, but also how we evaluate the next generation of health technologies and tools for patients and providers alike.

Designing feedback for patient-provider interactions

Work at UW, in collaboration with Microsoft Research, investigated the design of real-time feedback of interventional systems to improve patient-provider communication. Specifically, Entendre is a wizard-of-oz simulated system designed to provide feedback to doctors on the quality of their communication during patient-provider interactions. [22]

Based on a system for capturing "honest signals" in video conferencing [5] Entendre maps nonverbal cues (e.g., talk time, turn-taking, pitch, gesture, nodding) to relational communication signals, including conversational control and interpersonal affiliation [1, 3] that are associated with patient-centered communication. In a feasibility study using Entendre in simulated encounters with standardized patients [15, 22] providers' demonstrated acceptability of visual feedback. Figure 2 shows how the system displays feedback to a provider during a clinic visit without detracting from patient interaction.

THE UNBIASED RESEARCH PROJECT

The goal of our UnBIASED project is to detect and highlight hidden bias in patient-provider communication with novel SSP technology that makes communication visible. Designed in collaboration

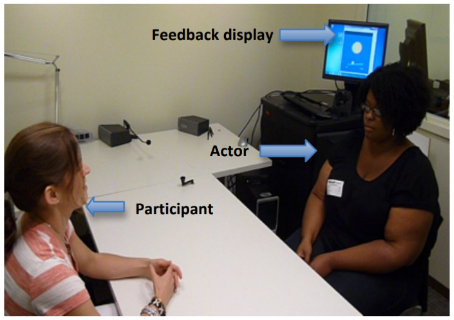

Figure 2: Entendre showing nonverbal behavior feedback to a provider [22]

with providers and underserved patients, this technology will automatically capture nonverbal and affective cues in clinical interactions, providing feedback to promote change through awareness and reflection. Building on our preliminary work, we will use our multidisciplinary expertise spanning SSP, Human-Computer Interaction, and the science of implicit bias in clinical communication, to engage patients and providers from academic and community clinics in Seattle and San Diego. To achieve this goal, we structure our UnBIASED project around three aims:

Aim 1: To develop & validate a computational model of bias in patient-provider communication – We will use existing datasets of recorded patient-provider visits to computationally model patient-provider interactions. This will be based on (a) social signals that reflect communication features (e.g., gesture, gaze, speech prosody, conversational dominance) and (b) Roter Interaction Analysis System [25] coding of the recorded interactions. We will validate our model with new patient-provider interaction data collected from clinics in low income, racially diverse neighborhoods. Finally, we will identify provider hidden biases based on factors like race, gender, sexual orientation, and socioeconomic status using the Implicit Association Test (IAT) [12] and link identified biases to our computational model.

Aim 2: To design feedback that effectively conveys biased behavior to patients and providers – Guided by human-centered design principles, we will design interventions that offer respectful, constructive, and timely feedback about bias in patient-provider communication. By including both providers and patients in the research, we will examine key intervention dimensions, including context of use, target user(s), workflow, timing, and presentation of feedback. Using participatory research methods, we will engage patients and providers to assess their feedback needs, co-design prototype interventions in collaboration with patients and providers, and then assess and refine prototypes with patients and providers.

Aim 3: To evaluate the efficacy of SSP technology in controlled and real-world settings – We will combine our model of hidden bias (Aim 1) with feedback (Aim 2) to build a functional tool for systematic evaluation. The "UnBIASED" tool, will assess interaction and display feedback to conversational partners. In a series of simulation studies, we will study our tool across scenarios designed to prompt varied levels of provider bias as they work with standardized patients in an education setting. Finally, we will perform a multi-site efficacy study to evaluate UnBIASED in primary care clinics serving low income, racially diverse patients in Seattle and San Diego.

All in all, the UnBIASED project will contribute a novel use for behavior sensing through SSP that brings human-centered visibility to hidden biases in clinical communication. We will validate a computational model of patient-provider communication tuned to detect bias, create concrete prototypes that convey feedback about those biases, and systematically test UnBIASED in simulated and real-world settings. We believe the findings will lead to new techniques to train providers, empower patients, enhance care quality, and improve equity.

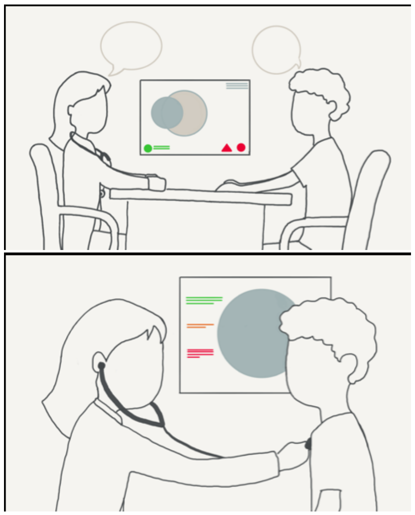

Figure 3: Envisioned interventional systems to be deployed in clinics which not only sense hidden bias but also prompt for reflection and behavior change

CHALLENGES AND OPPORTUNITIES

Feedback that is respectful, constructive, and timely is the cornerstone of clinical training [23]. Such feedback can raise provider awareness of their interactions with patients, and training on implicit attitudes can help providers be aware of their potential for bias [2, 10, 12, 13, 30]. Still, many socio-technical challenges remain to effectively achieve the goals set out.

First, computational sensing previously used in clinical encounters analyzed individual signals (such as gaze or speech) [8], rather than relational signals (such as mimicry) [4]. We have an opportunity to advance the sophistication of sensing with algorithms that focus on interpersonal social signals, tightly connected relational cues that consider both audible and visual expressions.

Second, prior work focuses exclusively on providers [8, 15]. We will engage patients alongside providers to design systems that provide feedback that is respectful, constructive, and timely for both stakeholder groups, reflecting best practices for effective clinical feedback [23].

Third, while ambient interfaces are less distracting, any intervention that occurs during conversation risks interruption. Our feedback could be reflective, something that providers and patients see after the visit, or at the end of the day. It could take on other non-visual forms (auditory, haptic, etc). Co-design processes should also reduce the influence of the research team's own biases on feedback design.

Finally, deployment of any intervention in healthcare settings requires a thorough examination of potential negative impact on care. Collaboration with clinic champions is needed to plan future trials, including development of protocols, workflows, and outcome metrics. Using SSP for hidden bias presents the potential to advance biomedical informatics methods, improve computational behavior sensing, and generate designs that can mitigate persistent health disparities.

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