Purposeful AI

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ABSTRACT

The potential of AI to improve people's lives is unlimited. However, designing AI-infused systems to realize this potential *for all* is challenging, and it is particularly challenging within under-served minority communities. Revisiting algorithms and data sources to eliminate biases in AI is an important step toward expanding its benefits. However, this leads to the realization that some applications, although unbiased, may simply not be what marginalized communities need. Marginalized communities live in a unique socioeconomic and cultural context and have difficulties taking advantage of traditional AI-powered systems due to language, digital literacy, or other barriers. Additionally, the systems that currently exist usually fail to address the unique challenges in these communities. Therefore, designers and researchers in AI must understand that a fundamental dimension of fairness and ethics is to empower and lift the lives of under-served populations through purposeful human-AI research. This research not only recognizes the unique intersectionality and needs present in each community, but also treats them as the primary audience by overcoming traditional barriers between researchers and underserved communities.

This SIG proposal aims to initiate a multidisciplinary discussion around the design of AI systems that are *purposefully* targeted to marginalized populations. Within this discussion, our objective is to better understand how to conduct research to support and serve these communities – particularly if we are not members of such communities; and challenge the effectiveness of techniques like user-centered design in the context of AI-infused systems when the designer is not a member of the user community. In addition, we will delve into ways of translating research into practical applications to create a positive impact within these communities and narrow the disparities that exist in the optimal utilization of AI to improve lives for different communities.

CCS CONCEPTS

• **Human-centered computing**; • **Computing methodologies** → **Artificial intelligence**; **Natural language processing**; **Distributed artificial intelligence**; **Philosophical/theoretical foundations of artificial intelligence**;

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KEYWORDS

ethics, artificial intelligence, applications, communities, fairness, equity

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1 INTRODUCTION

The rapid advance in artificial intelligence is bringing about transformative, and sometimes disruptive changes across various domains and industries. GPS-based navigation, face recognition, health monitoring and physical training systems, and the recent surge of interest in large language models are just a few examples that are revolutionizing how people navigate through their daily routines. Many AI solutions are powered by the collective information of large communities. For example, recommender algorithms are capable of learning user preferences and interpreting user intent [10] by analyzing patterns of behavior of many users. This allows individuals to optimize their access, filter, and utilization of relevant information. Artificial intelligence and machine learning are also increasingly utilized to enhance learning and education [4]. Student's data is computationally analyzed to better understand the learning progress of each individual and provide customized instructional support with AI-assisted evaluation and conversational teaching assistants and learning partners. To improve the performance of AI models, many of these AI systems take into account user feedback through the user interfaces, such as up-voting or down-voting AI-generated predictions, clicking on or dismissing the recommended content, or explicitly submitting feedback to the developers [10]. All of these advances have transformed people's lifestyles and have augmented their ability to sustain them.

This transformation has come, to some extent, to the detriment of some minority populations [2]. These are minorities that have been historically discriminated against by their race, culture, or other aspects of their social context, implicitly or explicitly, at different stages of the data and machine learning pipelines, and the design and development processes of AI-infused systems [1]. For example, biases in data can propagate to the AI models for healthcare systems [16], policing [3], and university admissions[6], to name a few. The response to these shortcomings has sparked an interest in the concept of fairness as applied to artificial intelligence [15]. This concept deals with the prevention and mitigation of biases in data and machine learning models, and pre-assessing potential harms that can be caused by such systems [13].

Despite the ongoing endeavor to enhance fairness and ethics in AI systems, the above-mentioned advances do not necessarily result in evident improvements in the lives of disadvantaged communities. For example, automatic speech recognition software fails speakers of African American Vernacular English, due to a lack of cultural context and the ability to recognize prosody and grammatical structures present in the language [9]. Moreover, although some individuals adapt their speech to optimize the performance of the Automatic Speech Recognition (ASR) systems, they feel frustrated and angry when using the technology [12]. Another example is that of communities of low-literacy individuals. They lack the fundamental skills to utilize the AI technologies described above optimally. They lack the reading and writing skills to use many text or voice-based interfaces to their benefit. Their lack of the ability to decode and spell languages, and to articulate their thoughts, leads to a poor experience with both written and voice-based search engines [8]. In addition, insufficient digital literacy also poses hurdles for individuals to comprehend the advantages and appropriate utilization of intelligent systems [11]. Consequently, these individuals are often susceptible to scams, frustration, and mistrust of technology to the point that they may even discontinue the use of such interfaces altogether [19]. In sum, the communities described in these examples are poised to fail at utilizing most of these applications, since they are language-based, require high levels of literacy, and/or assume certain social or cultural norms that do not apply to them.

These shortcomings suggest that to improve the lives of disadvantaged communities with AI, the technology must be **purposefully aimed** at these communities. That is an AI designed *from the ground up* for these communities. The SIG proposed here aims to make this discussion more salient among the community of researchers in AI and human-centered design. Rather than mitigating existing biases and protecting certain communities as the vulnerable, this SIG revisits the inherent sociotechnical power dynamics between AI system designers and disadvantaged communities, to explore new ways to design AI-infused systems for diverse populations and serve community-specific needs.

2 THE UNIQUE CHALLENGES OF PURPOSEFULLY DESIGNING AI FOR DISADVANTAGED COMMUNITIES

Understanding disadvantaged communities and designing technology for them is far from trivial. Although this has been the intent of participatory design [17], research and the design of technology for disadvantaged communities are largely carried out from the perspective of privileged researchers and it "neglects the challenges associated with envisioning equitable design solutions among underserved populations" [7]. In part, this happens due to the narrow lens with which problems are examined. Thus, researchers in equitable AI have called to diversify the disciplines involved in AI research [15], and in particular, it is essential to include a multidisciplinary team whose individuals are deeply invested in making technology more fair and equitable [18].

In addition to diversifying teams, the power relationships between those that have been historically marginalized and those with privilege –in this case, the researchers or designers of technology cannot be ignored [7]. Overcoming this relationship may require becoming more than a researcher in a particular community. It may require becoming a trusted partner and advocate. For example, Xu et al. examined the role of inclusive survey recruitment methods in reaching marginalized voices [20]. There is a need for more research efforts like these to understand and analyze the intersectionalities present in different marginalized communities, and develop responsible and effective research methods accordingly.

In addition to the above-mentioned *structural precarity*, researchers also face *institutional legitimacy* when conducting research with underprivileged populations [5]. Because disadvantaged communities often experience unique vulnerabilities, the Institutional Review Boards (IRB) are especially strict and request *precisely* how the interventions will be conducted. However, determining the words, language, gestures, and other outputs generated by an AI and to be shown to the participants is often at odds with the vision of an autonomous and non-deterministic system. Moreover, when targeting communities with additional medical conditions, the IRB review process can become even more complex, involving multiple steps such as obtaining medical records and collaborating with medical schools.

The few challenges outlined here require time and effort that goes beyond that of traditional AI research. First, gathering, interacting, and agreeing with an interdisciplinary team can be challenging and time-consuming. It may not only involve looking for those people, but also mentoring minority students. Second, becoming a trusted partner of the community takes time and an investment in social capital. In many ways, it can be a life choice. Lastly, dealing with institutional barriers can be frustrating and lead to unexpected delays in research.

Just like humans need to receive education and training to specialize their skills to interact with these populations, AI algorithms, and datasets need to be prepared from the ground up to intentionally serve members of these communities. This includes intelligent user interfaces that are culturally appropriate for specific groups, language models specifically designed to understand minority populations, recommender systems that are less sensationalistic and more considerate and useful towards vulnerable groups, as well as new applications that are uniquely aimed at the needs of specific marginalized communities.

3 RESEARCHER REFLEXIVITY IN PURPOSEFUL AI

The design of intelligent user interfaces is especially critical as it is the frontier communication channel between the end users and the AI system. It is important to recognize that the design process is not isolated from a particular social context. Most commonly the context of the researchers plays an important role in the methods [20] and lens [14] through which observations and interpretations are made. However, with a lack of diversity in researchers and research methods, most of these interfaces have not been designed with diverse populations and social contexts in mind, not to mention purposefully designed for a specific community.

While the sub-field of equitable AI has been striving to address some of the biases and unintended consequences of AI algorithms on marginalized populations, there is a need for broader discussions on AI research that is tailored to specific sociocultural contexts and aims to solve unique problems within the intersection of those contexts.

The SIG intends to foster a discussion around the purposeful design of AI for marginalized populations. That is researchers, scholars, industry practitioners, and designers, who scrutinize the needs of a particular marginalized community and, through community-oriented research and design, produce theoretical models, methodologies, and intelligent user interfaces that are culturally appropriate and cater to the unique needs and intersectional contexts of a specific disadvantaged community.

In order to comprehensively address the complex questions at hand, it is imperative to engage a diverse and multidisciplinary group of experts in a holistic exploration of the topic regarding its theoretical underpinnings, human behavior and cognition, technical aspects, and practical implications. The main objective of this SIG is to generate a set of thought-provoking questions that propel the discussion forward, thereby promoting a fruitful exchange of ideas that culminates in the collaborative development of a comprehensive design and evaluation framework for purposeful AI.

We prepared questions along five dimensions that help us initiate the discussion: **(a) Power:** How can researchers from a socially empowered culture understand the problems of and accurately identify solutions for marginalized communities? **(b) Trust:** What are the limitations of user–centered and participatory design when the users do not trust the designers? **(c) Community Impact:** How can we translate research into a positive impact for these communities? **(d) Sustainability:** How can we create a pipeline of diverse researchers to continue working on these problems? **(e) Validity:** How do we operationalize guidelines and best practices to ensure well-intentioned research can be responsibly conducted and bring culturally relevant outcomes to the target community?

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