Where is the Human? Bridging the Gap Between AI and HCI

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ABSTRACT

In recent years, AI systems have become both more powerful and increasingly promising for integration in a variety of application areas. Attention has also been called to the social challenges these systems bring, particularly in how they might fail or even actively disadvantage marginalised social groups, or how their opacity might make them difficult to oversee and challenge. In the context of these and other challenges, the roles of humans working in tandem with these systems will be important, yet the HCI community has been only a quiet voice in these debates to date. **This workshop aims to catalyse and crystallise an agenda around HCI's engagement with AI systems**. Topics of interest include explainable and explorable AI; documentation and review; integrating artificial and human intelligence; collaborative decision making; AI/ML in HCI Design; diverse human roles and relationships in AI systems; and critical views of AI.

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CCS CONCEPTS

• **Information systems** → **Information systems applications**;

KEYWORDS

artificial intelligence; human computer interaction.

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BACKGROUND

Advances in deep machine learning as well as hardware have pushed the development of artificial intelligence (AI) systems. By developing machine learning (ML) techniques to process large volumes and modalities of data, by turning voluminous sources of data into signals, and by providing robust predictions of critical outcomes, AI systems can both supplement and replace human decision-making [41]. AI has begun to make great strides in many problems of societal significance and has already made contributions to challenges such as development and poverty [26], education [23], agriculture and the environment [14, 38], and healthcare [27]. At the same time, AI has begun to expand our ability to make important decisions in business, law, finance, and politics [4, 5, 8, 18, 28, 30, 37], to more easily reach and help vulnerable populations [11, 12, 25], to predict health and wellbeing [7, 13], to more quickly detect people at risk of poor outcomes and provide early interventions [36], and sometimes to identify actionable or personalized solutions [6, 24].

However, with the pervasive adoption and prevalence of AI in real-world contexts, these systems have also raised the concerns among both researchers and practitioners for issues of bias, accountability, fairness, and discrimination. To solve these problems, machine learning researchers and practitioners have focused on providing mathematical insights to correct issues such as bias, discrimination, and transparency of algorithm choice. These researchers have focused on improving the algorithms themselves to correct for bias [16, 22, 35] and to improve interpretability [33, 44]. This area has seen tremendous growth in the past few years as demonstrated by the many outlets for such work, including the ACM Fairness, Accountability, and Transparency (FAT*) conference[1] and multiple iterations of FAT-workshops (FAT/ML for recommendations, FATREC for recommender systems, etc.) at premier ML conferences. This work is providing important computational prerequisites and scaffolding necessary for responsible deployment of machine learning.

[1] www.fatconference.org

However, the **human** is still a critical, if not the central, component of many scenarios where AI/ML is being advocated either as an assistant or as an augmentation for human intelligence. While most AI/ML systems offer robust empirical performance for real-world problems, many of these approaches are developed opaquely and in isolation, without appropriate involvement of the human stakeholders who use these systems or are emost affected by them. As the following fictional exemplar implies [31]: "*[..] we can't just tell the doctor 'my neural network says this patient has cancer!' The doctor just won't accept that!*". Human involvement in AI system design, development, and evaluation is critical to ensure that the insights being derived are practical, and the systems built are meaningful and relatable to those who need them [21]. Some recent HCI work has focussed on adoption issues of this kind [40, 43], but it remains unclear how the characteristics of emerging AI technologies may interact with existing understanding around decision-support or expert systems in-the-wild.

It is also important to prevent unintended consequences and to alleviate risks stemming from bias, errors, irresponsible use, misaligned expectations, privacy concerns, and potential issues around lack of trust, interpretability, and accountability. Moreover, human activities and behaviors are deeply contextual, nuanced, and laden with subjectivity – aspects that many current AI/ML systems often fail to account for adequately [29]. We need to be able to incorporate AI systems into interactive, usable, and actionable technologies that function in the natural contexts of all human stakeholders in a bias-free manner. This, in turn, requires augmenting these systems with orthogonal but complementary human-centered insights that go beyond aggregated assessments and inferences to ones that factor in individuals' differences, demands, values, expectations, and preferences [17, 34]. The success of such systems in the real world requires multi-disciplinary partnerships who bring diverse perspectives to solve these problems which are as much human problems as they are AI.

Summarily, despite the importance of people in the development, deployment, and use of AI systems, Human Computer Interaction (HCI) is often not a core component of these research questions. AI researchers have recently begun to note this important gap in popular discourse, e.g., "*Despite its name, there is nothing 'artificial' about this technology – it is made by humans, intended to behave like humans and affects humans. So if we want it to play a positive role in tomorrow's world, it must be guided by human concerns.*"[2]. We argue, moreover, that comprehensive inclusion of HCI's unique perspectives are essential to solving these challenging societal questions. Therefore, through this workshop, we ask the fundamental question: *Where is the human in AI research?*

This one-day workshop will explore critical questions in bringing the human more into the development and deployment of AI systems, and work to unite HCI research methods and concerns with AI. Our workshop will support 25-30 participants across topical and methodological areas that relate to the interplay of HCI and AI — including machine learning and AI, HCI methods complementary to understanding AI/ML, critical algorithm studies, and domain applications such as employment and labor, future of work, health care, and moderation.

[2]https://www.nytimes.com/2018/03/07/opinion/artificial-intelligence-human.html

GUIDING QUESTIONS AND RESEARCH AGENDA

Our workshop provides an opportunity for researchers and practitioners interested in the intersection of HCI and AI to come together to share interests and discuss ways to move the field forward. We provide a set of guiding questions for the community to consider:

(1) **Explainable, Explorable, and Interpretable**: What do humans need to effectively utilize AI insights? How can users explore AI systems' results and logic to identify non-obvious failure modes? What approaches best span the gulf between how an AI system *works* and what it *means*? Examples might be undesirable impacts on latent groups not corresponding to categories in the dataset [39], difficult-to-spot changes ('concept drift'), or feedback loops in the socio-technical phenomena the AI system is modeling over time [19].
(2) **Documentation and Review:** Some work is beginning to understand how models and datasets might be documented in context [20, 32]. Something less considered, but called for by practitioners on-the-ground [40], is how social routines supporting oversight, human-AI synergy, etc, might be effectively packaged up and documented, particularly in new or changing environments with high staff turnover, or in the context of model trading.
(3) **Integrating Artificial and Human Intelligence**: AI systems and humans both have unique abilities and are typically better at certain complementary tasks than others. For instance, while AI systems can summarize voluminous data to identify latent patterns, humans can extract meaningful, relatable, and theoretically grounded insights from such patterns. What kind of research designs or problems are most amenable to and would benefit the most from combining artificial and human intelligence? What challenges might surface in attempting to do so?
(4) **Collaborative Decision Making**: How can we harness the best of humans and algorithms to make better decisions than either alone? How do we ensure that when there is a human-in-the-loop — such as in complex or life-changing decision-making — they remain critical and meaningful, while creating and maintaining an enjoyable user experience? Where is the line between decision support anticipating the needs of the user and it removing the user's ability to bring in novel, qualitative critical knowledge to enable the system's goals [cf. 9, 10]?
(5) **AI in the HCI Design Process**: How can algorithmic tools be made more readily accessible during the HCI design process to those whose expertise lies outside of machine learning, and computer science more broadly [15, 42]? What are some successful AI/ML-HCI collaborations? What made them work? Where do the barriers exist and how might we overcome them?
(6) **Representing Diverse Human Roles and Relationships in AI Systems**: AI systems often involve humans in capacities other than the traditional "user" [1, 3]; for instance, individuals who conceptualize the system, the developers, the people who evaluate the underlying machine learning models, and those whose data the system draws from to make inferences. What

approaches — across the design, implementation, evaluation, and deployment processes — help account for the variety of relationships that people have with AI systems?

(7) **Critical Views of AI**: Work in fields such as science and technology studies (STS), communication, media studies, and other areas has examined the social, political, and economic ramifications of AI systems [21]. To date, little of such work has been incorporated into HCI [2]. How can critical perspectives be brought into a meaningful, productive dialog with design- and implementation-oriented work? In short, how do we foster a productive dialog among researchers across various disciplines?

Call For Participation

We invite submissions for a one-day workshop to discuss critical questions in bringing humans into the development and deployment of artificial intelligence (AI) and machine learning (ML) systems. Relevant human roles include those who envision such systems, those who develop and evaluate the underlying models, those whose data are analyzed, those who view the results, those who make decisions based on the results, and others.

Papers should be 2-4 pages long in the CHI Extended Abstract format, and may address topics related to the intersections of HCI, AI, and machine learning. This includes but is not limited to: ongoing work; reflections on past work; combining methods from HCI and design to AI; and emergent ethical, political, and social challenges. A set of guiding questions has been provided on the workshop website.

The due date for submissions is no later than February 12, 2019 by email. Participants will be selected based on the quality and clarity of their submissions as they reflect the interests of the workshop. Notifications will go out no later than March 1, 2019. At least one author of each accepted position paper must attend the workshop, and all participants must register for both the workshop and at least one day of the conference.

ORGANIZERS

This group of workshop organizers was selected to reflect expertise at the intersection of AI and HCI, and also to represent the diversity we hope to recruit for participants. They have a strong past and current history of collaboration in various scope, capacities, and formats on projects at the intersection of AI and HCI. Additionally, they also have experience running successful workshops at CHI, CSCW, and other HCI conferences.

Kori Inkpen is a Principal Researcher at Microsoft Research where she leads the Social Technologies research team. Dr. Inkpen's research interests are currently focused on Human+AI Collaboration to enhance decision making, particularly in high-impact social contexts which inevitably delves into issues of Bias and Fairness. Kori has been a core member of the CHI community for over 20 years.

Munmun De Choudhury is an Assistant Professor in the School of Interactive Computing at Georgia Tech where she directs the Social Dynamics and Wellbeing Lab. Dr. De Choudhury's research interests lie at the intersection of machine learning, social media, and health, with a focus on assessing, understanding, and improving mental health from online social interactions.

Stevie Chancellor is a PhD Candidate in Human Centered Computing at Georgia Tech. She researches data-driven algorithms to understand deviant mental health behavior in online communities. Her work combines techniques from machine learning and data science with human-centered insights around online communities and mental health, focusing on identifying and predicting content from pro-eating disorder communities on social networks.

Michael Veale is a doctoral researcher in responsible public sector machine learning at the Dept. of Science, Technology, Engineering & Public Policy at University College London. His work spans HCI, law and policy, looking at how societal and legal concerns around machine learning are understood and coped with on the ground.

Eric P.S Baumer is an Assistant Professor of Computer Science and Engineering at Lehigh University. His research focuses on interactions with AI and machine learning algorithms in the context of social computing systems. Recent work includes using computational tools to identify the language of political framing, and studying technology refusal in the context of Facebook.

WORKSHOP STRUCTURE

Proposed Schedule and Activity Breakdown

Invited Speaker. We will recruit an invited speaker from the interdisciplinary area of HCI and machine learning, who will be invited to give a talk related to interpretable and transparent machine learning which is a necessity to better enable Human+AI Collaboration. We will follow this with a Q&A period for the participants of the workshop.
Researcher "Speed Networking". Participants will line up and get 60 seconds to introduce themselves to another member of the workshop as well as a brief description of their research and what they hope to get out of participating in the workshop. This will serve as an ice breaker activity for participants, and we have found this particular style of introduction very effective in past workshops.
Case Studies. To further develop the implications of HCI and AI, we will invite small groups to work through challenging case studies and propose important contributions needed from the HCI community. These are real-world examples of AI's integration into decision-making processes with high stakes and risks. Possible topics include:

(1) Cancer and Mental Health AI – What to do when the system disagrees with the doctor/psychiatrist?
(2) Criminal Justice – How to avoid bias and enhance fairness in parole or risk assessment systems?
(3) Surveillance and Crime Prevention – What concerns emerge around AI for such tasks as anticipating domestic or child abuse?
(4) Algorithmic Content Curation – How to balance the various demands in curating and ranking social media news feed content?
(5) Computational Journalism – How to develop systems that balance concerns of journalists, of readers, and of those whose data are analyzed?

One or more case studies will be selected based on participant interest in the position papers.
Next Steps. Brainstorm important next steps to continue these conversations and strengthen the community of HCI researchers working on Human+AI problems and facilitate rich collaborations with others disciplines. Additionally, we will discuss ways we can have broader impact by ensuring that this topic is central to HCI education.

Post Workshop Plans

We plan to take the ideas generated from the workshop and write a public facing blog post (e.g., a Medium article) on the argument "Where is the human in the AI". We will also take insights gleaned from the next steps brainstorming and prioritize a few action items that members of the workshop will engage in after the workshop. This could include plans for follow-up symposiums, multi-disciplinary workshops or curriculum tools.

PROPOSED SCHEDULE

0900 - Welcome and Introduction
0915 - Keynote speaker + Q & A
1015 - Mid-morning break
1030 - Speed networking for introductions
1100 - Brainstorm key areas for HCI growth
1200 - Lunch break
1300 - Case-Study Breakout Groups
1430 - Mid-afternoon break
1500 - Report back from Case-Studies
1600 - Brainstorm next steps
1700 - Workshop concludes

Website. A website will be created for the workshop as both a repository for materials and to solicit participation (http://aka.ms/WhereIsTheHuman). The website will include the Call for Papers (detailed on the sidebar), resources for case studies, the biography of our invited speaker, position papers, and post-workshop plans and updates.

Recruitment. We will promote the workshop through a variety of channels related to HCI (Facebook CHI Meta page; Researchers of the Socio-Technical Facebook Page; Twitter), industry professionals (mailing lists), and colleagues from the machine learning community (FAT*, AIES, ICML, ACL). Local participation will be encouraged through the Scottish SICSA-HCI mailing list.

Participants will be selected based on their prior experience and interest in the workshop as well as the quality of their submissions. We will focus on recruiting from a diverse group of participants, with a balance of students and faculty; industry practitioners and academic audiences; contribution areas within HCI and AI research; and representation of different cultures, genders, and races.

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