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Introduction to this special issue on unifying human computer interaction and artificial intelligence

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McCarthy (1998) defined Artificial Intelligence (AI) as both "the science and engineering of intelligent machines, especially computer programs" and the "computational part of the ability to achieve goals in the world." Today, AI is increasingly deployed across many domains of direct societal relevance, such as transportation, retail, criminal justice, finance, and health. But these very domains that AI is aiming to revolutionize may also be where human implications are the most momentous. The potential negative effects of AI on society, whether amplifying human biases or the perils of automation, cannot be ignored, and as a result, such topics are increasingly discussed in scholarly and popular press contexts. As the New York Times notes: "… if we want [AI] to play a positive role in tomorrow's world, it must be guided by human concerns" (Li, 2018).

The relationship between technology and humans is the direct focus of human–computer interaction (HCI) research. However, conversations about the relationship between HCI and AI are not new. For the past 20 years, the HCI community has proposed principles, guidelines, and strategies for designing and interacting with user interfaces that employ or are powered by AI in a general sense (Norman, 1994; Ho¨ o¨ k, 2000). For example, an early discussion by Shneiderman and Maes (1997) challenged whether AI should be a primary metaphor in the human interface to computers: Should interactions between a human and a computer mimic human–human interaction? Or are there practical or even philosophical objections to assigning human attributes and abilities to computers? Putting aside these fundamental questions about what human-AI interactions might look like, Norman (2014) and Ho¨ O¨ (2000) adopt a more practical approach to designing AI systems. They recommend building in safeguards like verification steps or regulating users' agency so as to prevent unwanted behaviors or undesirable consequences arising from these systems. More broadly, other HCI researchers have contrasted the differences in approaches and philosophies adopted by HCI and AI researchers, particularly around how we understand people and create technologies for their benefit (Winograd, 2006). Grudin (2009) also described alternating cycles in which one approach flourished, while the other suffered a "winter," characterized by a period of reduced funding, accompanied by low academic and popular interest. Building upon Grudin, Winograd (2006) contrasted the strengths and limitations of each, as well as the relevance of rationalistic versus design approaches offered by AI and HCI, respectively, when applied to "messy" human problems. Winograd's overall conclusion was rather surprising: he conjectured that the two fields are not so distinct. He concluded that their philosophies are both rooted in common attempts to push the computer metaphor onto all of reality, as evidenced in most twentieth-century science and technology research. Formative and notable work by Horvitz (1999) also attempted to reconcile many of the seeming differences between HCI and AI by highlighting key challenges and opportunities for building "mixed-initiative user interfaces." These are interfaces that enable users and AI to collaborate efficiently. Horvitz states principles for balancing autonomous

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actions with direct manipulation constructs, gauging ideal actions to pursue in light of costs, benefits, and uncertainties.

Despite early efforts to bridge this divide, we are yet to witness a convincing *marriage* between HCI and AI. Efforts like Stanford's Human-Centered Artificial Intelligence (HAI) and MIT's College of Computing that explicitly focus on human-centric AI research are commendable. But we, like other scholars (Ernala et al., 2019; Fox et al., 2017; Green, 2018; Inkpen et al., 2019; Tufekci, 2015), posit that simply introducing human guidance or human sensitivity into AI is not sufficient to realize AI's full potential and prevent its unintended consequences. While most AI-based approaches offer promising methods for tackling real-world problems including those of concern to HCI researchers, many of the technologies they enable have been developed in isolation, without appropriate involvement of the human stakeholders who use these systems and who are the most affected by them (Lee et al., 2019; Woodruff et al., 2018). Furthermore, many AI systems generate automated inferences and function under uncertainty (Chancellor et al., 2019) – scenarios where false positives or negatives can have severe implications for humans using them, leading to unpredictable, disruptive, hostile, and even dangerous system behaviors.

This renewed interest is also warranted because the landscape of both AI and HCI research has changed a great deal since those discussions 20 years ago. The field of AI has developed very rapidly in recent years, with exponential gains in data sizes (e.g., ImageNet (Deng et al., 2009)) and compute power (e.g., Graphical Processing Units or GPUs (Cui et al., 2016)). And algorithms and machine learning methods have also evolved significantly (Abadi et al., 2015; Paszke et al., 2019). This has caused a wide diversity in the design, functioning, and complexities of AI systems. Naturally, a higher propensity for failures has resulted. According to media reports, these range from embarrassing (e.g., autocompletion errors (Amershi et al., 2019)), through outright offensive (e.g., Microsoft's "racist" chatbot Tay (Wolf et al., 2017)) to fatal (e.g., self-driving cars failing to "see" pedestrians who are people of color (Hawkins, 2019)). To summarize, the vision of engaging, adaptive, and useful mixed-initiative interfaces (Horvitz, 1999) that work for the benefit of their users (Winograd, 2006) is yet to be realized.

Existing AI systems are already providing multiple challenges and opportunities for the HCI community. These include understanding sources of bias in AI systems (Scheuerman et al., 2019), conceptualizing how to adequately represent different users' perspectives in building new AI systems (Lee et al., 2019; Woodruff et al., 2018), developing methods for incorporating and balancing stakeholder values in algorithm design (Zhu et al., 2018), designing transparent interfaces that communicate how AI systems work to stakeholders (Cheng et al., 2019), or finding ways to address people's fleeting trust in opaque online recommendation and content curation algorithms such as Facebook's News Feed (Eslami et al., 2015). At the same time, AI researchers have recently made huge investments in the topics of fairness, accountability, and transparency of AI systems[1], while acknowledging the value of identifying human-centered principles that can guide how AI systems are built, evaluated, and deployed.

Complementing these emergent efforts, this special issue's central thesis is that human involvement in AI system design, development, and evaluation is critical to ensure that AI-based systems are practical, with their outputs being meaningful and relevant to those who use them. Moreover, human activities and behaviors are deeply contextual, complex, nuanced, and laden with subjectivity. These characteristics may cause current AI-based approaches to fail, as they cannot adequately be addressed by simply adding more data. As a result, to ensure the success of future AI approaches, we must incorporate new complementary human-centered insights. These include stakeholders' demands, beliefs, values, expectations, and preferences – attributes that constitute a focal point of HCI research – and which need to be a part of the development of these new AI-based technologies.

The same issues also give rise to pressing new questions. For instance, how can existing HCI methodology incorporate AI methods and data to develop intelligent systems that improve the

[1]https://facctconference.org

human condition? What are the best ways to bridge the gap between machines and humans when designing technologies? How can AI enhance the human experience in interactive technologies; and further, could it help define new styles of interaction? How will conventional evaluation techniques in HCI need to be modified in contexts where AI is a core technology component? What existing research methods might be most compatible with AI approaches? And, what will be involved in training the next generation of HCI researchers who want to work at the intersection with AI? Of course, the concepts of "design," "interaction," and "evaluation" continue to be interpreted by different HCI researchers and practitioners in multiple related but non-identical ways. Nonetheless, how unifying AI and HCI research will influence these interpretations remains an open but pertinent question.

1. Articles in this special issue

This special issue is motivated by the premise that the currently disjunct philosophies and research styles of the HCI and AI fields, along with the current context, both academic and societal, demand renewed attention to unifying HCI and AI. We hope the articles featured in this issue extend prior attempts to bridge the two fields, adding to the recent traction AI has achieved in tackling challenging human problems. In doing so, we seek to engage both HCI and AI researchers working on theoretical, empirical, systems, or design research that draws upon both perspectives. We hope the original research presented in this special issue can initiate a dialog to bridge the gap to help integrate this emerging space.

The HCI community recognizes that designers struggle to work with AI and Machine Learning (ML) techniques (Dove et al., 2017). Despite attempts to integrate HCI and AI, these designers experience challenges in incorporating ML into common user experience (UX) design paradigms. These challenges can arise because ML models are constantly evolving, and UX designers may be unaware of, or uncomfortable with, the restrictions of the environment, laws, and regulations guiding ML operations in real-world scenarios (Amershi et al., 2019). Consequently, Lingyun Sun, Zhibin Zhou, Yuyang Zhang, Xuanhui Liu, and Qing Gong (Sun, Zhou, Azhang, Liu & Gong, this issue) argue that conceptual design methods for empowering UX with ML need to be tailored to these unique attributes of ML. Accordingly, they adapt concepts from design thinking (e.g., service design, material-driven design) to integrate existing research and guidelines for ML-human interaction. Their goal is to help designers understand the changing and complex nature of ML and to combine information about ML, users, and specific real-world contexts in a holistic way. Targeting novice designers, the authors develop ML Lifecycle Canvas, a conceptual design tool derived from Material Lifecycle Thinking (MLT) that regards ML as a constantly growing material with an iterative "lifecycle." The tool creates a visual schematic incorporating the perspectives of ML, users, and the scenario, detailing the ML lifecycle from data annotation to ML model update. On comparing this tool with a typical conceptual design tool in workshops involving 32 participants, the authors find that exposure to the ML Lifecycle Canvas enhances both understanding of ML and helps designers tackle ML-related UX issues.

The challenges faced by designers in building AI systems also lead us to the following question: How can we develop new methods, tools, and processes to help designers better innovate with AI? Jing Liao, Preben Hansen, and Chunlei Chai (Liao, Hansen & Chai, this issue) develop a framework describing explicit roles of AI in design ideation as (i) representation creation, (ii) empathy triggers, and (iii) engagement. They evaluate their framework in an empirical study of 30 designers with concurrent Think-Aloud protocols and behavior analysis. The study reveals opportunities for AI to support human creativity and decision-making in the early design stages.

Complementarily, AI systems have rarely considered the underlying principles of end user involvement that is core to HCI system design. To address this, the central premise of the work of Sachin Grover, Sailik Sengupta, Tathagata Chakraborti, Aditya Mishra, and Subbarao Kambhampati (Grover, Sengupta, Chakraborti, Mishra and Kambhampati, this issue) is that existing AI planning systems rarely provide decision-support to end user stakeholders, and instead have largely focused on end-to-end plan generation, with little human involvement, beyond making such systems merely "human-aware." In their article, the authors investigate whether an automated planner can support the human's decision-making process, despite not having access to the complete domain and preference models, while the humans control the process. The work makes important contributions to naturalistic decision-making scenarios such as disaster response where the cognitive overload of the human can negatively affect the quality of decision-making.

A different perspective is that the specification and development of AI systems are held back by an inability to view the problem in a human-centered manner. Eric Baumer, Drew Siedel, McLean Donnell, Jiayun Zhong, Patricia Sittikul, and Micki McGee (Baumer, Siedel, Donnell, Zhong, Sittikul, & McGee, this issue) develop a design process to support topic modeling and visualization for interpretive text analysis. The tool's primary aim is not to offer a definitive corpus-topic analysis, but rather it supports the iterative processes used by social scientific and humanist researchers to develop interpretations. The paper also suggests a novel application of machine learning techniques to support interaction design through visualization.

A different way to involve humans in AI is suggested in Gonzalo Ramos, Christopher Meek, Patrice Simard, Jina Suh, and Soroush Ghorashi(Ramos, Meek, Simard, Suh, & Ghorashi, this issue). This paper investigates how interactive machine teaching (IMT) can leverage unique human capabilities, allowing non ML experts to build ML models. The authors built an IMT system and used it as a design probe to highlight further opportunities and challenges with such systems. This article provides a clear example of how we can synergistically combine AI and human capabilities, so that everyday end users can build intelligent systems for their own contexts.

This special issue also covers research involving specific user populations for whom both the HCI and AI communities have identified direct opportunities for research as well as impact. AI-powered systems, such as intelligent virtual agents (IVAs), are increasingly used commercially in essential domains such as health care. Older adults are an exemplar of a potential user group to benefit from these technologies. However, there is a limited understanding of how to address the socio-technical challenges older adults might face in the development of such AI-powered systems. Jaisie Sin and Cosmin Munteanu(Sin & Munteanu, this issue) studied how older adults use and perceive an IVA. Specifically, they uncovered socio-technical issues relating to each of the six stages of the information search process which helps to better contextualize older users' interaction with IVA interfaces. We also see AI entering the field of employee management as addressed in the article by Lionel Robert, Casey Pierce, Liz Marquis, Sangmi Kim, and Rasha Alahmad (Robert, Pierce, Marquis, Kim, & Alahmad, this issue). Optimizing AI for work organizations can lead to unfairness to workers resulting in personal burnouts and worker turnover. The article addresses distributive, procedural, interactional fairness and proposes a design agenda for organizational scenarios. These designs must work effectively inside work compliance structures (legal, regulation, and policies) with an audit friendly AI which lays design groundwork for future AI approaches to support fairness in the workplace.

2. Issues for future research

We believe this special issue is a first, but formative step revisiting the complex, evolving relationship between HCI and AI. Although we have identified and begun to address some emerging issues, the articles published here do not constitute an exhaustive representation of work happening at the intersection of these fields and there are future challenges on the roadmap that the communities should be investigating. Here, we identify open issues in hopes to inspire future research.

2.1. *A socio-technical, instead of a purely technical mindset in AI system design*

Many AI systems adopt a technical approach to solving real-world problems. Given the ethical challenges that have been rampant in recent media coverage, we instead advocate a "socio-technical" approach, where both the social context and technical aspects of the problem are combined. This includes designs that carefully consider factors like culture, people, and socio-economic situations and their effect on society. As a result, in order to successfully bridge HCI and AI, we must go beyond the technology-determinism perspective which makes its claims based exclusively on technological power and hype, and instead enhance our understanding of why the same AI technology may have such different results in similar contexts.

2.2. *Participatory AI system design – Stakeholders are key*

From its inception in the mid-1950s, AI has emphasized participatory design to simulate capacities of human intelligence, and to ensure that people can effectively use machines and their applications. However, recent efforts in employing AI to solve real-world problems have not leveraged participatory research designs. Participatory techniques – a method core to the HCI field, can be a critical way to overcome the weaknesses of traditional AI approaches. Such techniques can enable developers and users of AI system to co-create technologies and tools that are relevant to end users' personal and social contexts, while being motivating and useful (Lee et al., 2019; Zhu et al., 2018).

2.3. *Lowering disciplinary barriers to collaboration*

The ultimate success of AI depends on how it actually addresses real-world issues, after factoring in the scenarios' complexities, nuances, and implications. This needs deep, substantive collaborations across disciplines that include not only researchers who identify with the AI field but also domain experts, and even those who are critics of AI. Perhaps AI and HCI researchers might benefit from adopting team science approaches (Bo¨ Rner et al., 2010). Central to the mission is to also evaluate how cooperation between sciences and technologies and domains might either promote or hinder progress. From there, we can devise better approaches to team management by identifying the most efficient methodologies in research, training, and communication at a larger scale, allowing teams to bridge the long-standing disciplinary barriers between HCI and AI. This will enable us to improve the team dynamic allowing collaborative groups to reach the level of progress and innovation achieved by individual researchers, whether in the HCI or AI field. This goes beyond simple checklists for AI system or design guidelines, instead requiring committed collaboration to achieve the authentic unification of research across the two fields.

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