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# Artificial Intelligence for HCI: A Modern Approach

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**Abstract**

Artificial intelligence (AI) and Human Computer Interaction (HCI) share common roots and early work on conversational agents has laid the foundation for both fields. However, in subsequent decades the initial tight connection between the fields has become less pronounced. The recent rise of deep learning has revolutionized AI and has led to a raft of practical methods and tools that significantly impact areas outside of core-AI. In particular, modern AI techniques now power new ways for machines and humans to interact. Thus it is timely to investigate how modern AI can propel HCI research in new ways and how HCI research can help direct AI developments. This workshop offers a forum for researchers to discuss new opportunities that lie in bringing modern AI methods into HCI research, identifying important problems to investigate, showcasing computational and scientific methods that can be applied, and sharing datasets and tools that are already available or proposing those that should be further developed. The topics we are interested in including deep learning methods for understanding and modeling human behaviors and enabling new interaction modalities, hybrid intelligence that combine human and machine intelligence to solve difficult tasks, and tools and methods for interaction data curation and large-scale data-driven design. At the core of these topics, we want to start the conversation on how data-driven and data-centric approaches of modern AI can impact HCI.

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### Author Keywords

Artificial intelligence; Human Computer Interaction; crowd-sourcing; data-driven design and modeling; deep learning; algorithms and tools; design guidelines; sensing.

### CCS Concepts

•**Human-centered computing** → **Human computer interaction (HCI)**; *HCI theory, concepts and models*; Systems and tools for interaction design; •**Computing methodologies** → Artificial intelligence; Machine learning;

### Background

The rise of deep learning [14] and the recent advance of data-driven methods [5] have fundamentally transformed the field of artificial intelligence. This impact can be felt much beyond the field of AI itself, with deep-learning methods making user facing systems such as speech based interfaces, self-driving cars and personal robots not only feasible but actually usable. Thus new opportunities for research in HCI and at the intersection with AI emerge if the machine no longer is a deterministic data processing automaton but a complex system that is capable of carrying out tasks that were previously squarely in the domain of humans.

AI powered systems clearly pose new questions for HCI. However, we increasingly see how HCI researchers leverage modern AI approaches in order to tackle classic HCI problems, such as modeling human interaction behaviors [15], and emerging ones, such as hybrid intelligence [13] and data-driven design [20] or to adapt user interfaces to user preference and context [7].

#### *Interaction Behavior Modeling*

Modeling human behaviors in an interaction task has long been pursued in the field of HCI, which is fundamentally

part of the quest of AI for computationally modeling human intelligence. In addition to advancing the scientific understanding about human behaviors, these models can aid interaction designers in determining how usable an interface is without having to test it with real users, which can be expensive and effort consuming. While classic models such as Fitts' law [6] and Hick's law [10] offer robust estimates about human performance on task components such as motor control and decision making, they are insufficient to capture various factors that might come into play in a realistic tasks. Despite various attempts to expanding traditional models [2, 3], methods that are purely based on analytical insights are often constrained, particularly for accommodating factors that are not easy to articulate.

Recently, researchers have started to use deep learning approaches for modeling interaction behaviors. Li et al. used a hierarchical recurrent neural net to model list selection tasks [15]. In addition to offer superior modeling accuracy, the work revealed the potential of deep learning methods for uncovering analytical insights into memory learning effect. Researchers have also attempted to combine analytical with learned model components for more complex tasks such as grid searching [17]. Beyond human performance modeling, recent work has attempted to address other aspects of human behaviors on user interfaces, e.g., predicting human perception about UI interactivity [19].

While it is promising to use deep learning methods in human behavior modeling, there are several challenges. First, deep learning methods are often data hungry while interaction data is scarce compared to classic machine learning problems such as computer vision or natural language processing. Second, deep models are not easy to analyze. While better modeling accuracy is of great benefit, inter-

pretability of a model is crucial for HCI researchers to gain new knowledge and to advance the field.

#### *Data-Driven Design & Hybrid Intelligence*

Mining data from existing designs can expose designers to a greater space of divergent solutions [4, 11]. With the millions of websites and mobile apps available today, it is likely that almost any UX problem a designer encounters has already been considered and solved by someone. Generative models such as Variational Autoencoders trained on a large set of design examples can suggest design alternatives to assist designers in the design process. Systems based on these AI methods often involve staged automation that start by using human-powered support or “Wizard of Oz” techniques to scaffold need finding or data collection, and eventually transition into semi or fully-automated solutions informed by the collected data [20, 12].

Rather than using human solely for the purpose of data collection to train an AI system, hybrid intelligence incorporates human users, often crowd workers, as an essential and permanent component in an interactive system for complex design tasks [13]. A system powered by hybrid intelligence needs to synthesize responses from multiple people in order to achieve sufficient performance or availability for the system as a whole. Hybrid intelligence provides rich research opportunities on combining human and machine intelligence not only for them to collaborate on a task, but also for them to improve each other in a dynamic, interactive fashion.

While there have been an increasing number of works in using data-driven and hybrid intelligence for complex design tasks, how such a data and model-driven approach impacts the design of an interactive system remains unclear. We want to use the workshop to learn from successful and difficult cases, and share datasets and frameworks.

#### *Perceiving User Interfaces*

Systems that interact with users always rely on mechanisms for humans to specify their intentions. Traditional techniques, including mice, keyboards and touch screens, require the user to explicitly provide inputs and commands. However, modern deep-learning based approaches are now robust enough to inherent ambiguity and noise in real-world data in order to make it feasible to analyze and reason about natural human behavior, including speech and motion but also more subtle activities such as gaze patterns or bio-physical responses. Such approaches now allow to go beyond simple gesture recognition [18] and pattern matching approaches [21], which still require the user to memorize a set of specific commands, and to be able to analyze complex human activity in a more continuous and holistic fashion. For example understanding fine-grained hand articulation for use in VR and AR [8], understanding and modelling natural handwritten text [1], or to estimate [16] and even synthesize human gaze data [9]. Such methods then form the building blocks for novel types of interactive systems in which the human and the machine interact in a more immediate fashion, leveraging new question for HCI in terms of how to design such UIs. However, AI based techniques cannot only be used to sense user input but also to learn high level concepts such as user preference or, more generally speaking, to analyse the usage context to adapt the UI and to present information proactively, given the estimated user intention (e.g., [7]).

Machine learning and AI techniques hold great promise in shifting how we interact with machines from an explicit input model to a more implicit interaction paradigm in which the machine observes and interprets our actions. To achieve such a paradigm shift many challenges need to be overcome. For example, acquiring data of human activity is much more difficult than in other domains such as com-

puter vision or NLP and hence new ways to collect data and to make use of smaller datasets are of central importance to HCI-AI research. Furthermore, novel algorithms to capture and model high-level user state and behavior, including cognitive activity and user intent could drastically change what the UI emphasises. Last but not least many questions arise on how such intelligent systems can be made usable, discoverable and how to mitigate issues around privacy, user-autonomy and user-control.

#### *Workshop Goals*

With more and more work in the field starting to embrace AI-based methods for solving HCI problems, we see a fundamental shift of HCI methodologies towards more data driven and model centric. With these methods, we also see many hard HCI problems that can now be attempted. As a result, it is timely to bring together researchers to discuss new opportunities that these approaches enable and meanwhile new challenges that we face.

*Problem Taxonomies.* First and foremost, we aim to develop a taxonomy of HCI problems where these AI-based methods can have a significant impact. It can be a refinement and an extension of the set of topics we have presented above or new problems that are under-explored.

*Data & Method Challenges.* The workshop will provide a forum for researchers to share the challenges they face in their research. For example, it is important to discuss how to scale interaction datasets such that deep learning methods are more feasible. The workshop will also provide a learning opportunity for researchers to share their experiences with using these modern AI methods.

*HCI versus AI Contributions.* A critical issue that has constantly raised in the community is how an AI-based work is related to the HCI field and making meaningful contribution

to HCI, rather than being considered AI contributions. We want to gather thoughts on criteria for judging the value of these works.

*Interpretability.* Having analytical understanding about machine intelligence is an important topic both in the AI and the HCI field. We want to discover good examples about explainable AI in HCI problems, and gather thoughts on aspects that researchers would seek analytical understandings as well as how these findings can contribute new knowledge to our field.

*Sharing Tools & Datasets.* Lastly, through the workshop, we want to allow researchers to share methods, tools and datasets that have been useful in their work, which will benefit other researchers in the field.

## **Organizers**

The organizers of the workshop are well-known researchers in the field of Human-Computer Interaction, who have also worked and published in related fields such as artificial intelligence, machine learning, human computation, sensing, and data mining. These organizers have also served as members of the senior program committees or reviewers for premier conferences and journals in HCI, AI, and other related fields. Thus, the organizers are well qualified to bridge these multiple fields, and bring their expertise into advancing this topic.

Yang Li, Ph.D., is a Staff Research Scientist at Google Research, and an affiliate Associate Professor in Computer Science & Engineering at the University of Washington. He earned a Ph.D. degree in Computer Science from the Chinese Academy of Sciences, and conducted postdoctoral research in EECS at the University of California at Berkeley. His current research focuses on using deep learning methods to model human intelligence in interaction tasks.

Yang led the development of next app prediction at Google that is in use by tens of millions of users, which pioneered on-device interactive ML on Android. Yang has extensively published in top venues across both the HCI and ML fields, including CHI, UIST, ICML, NeuralPS, ICLR, CVPR and KDD, and has constantly served on the program committees of top-tier HCI venues including SCs and ACs at CHI and reviewers at ICML and NeuralPS.

Walter S. Lasecki, Ph.D., is an Assistant Professor of Computer Science and Engineering at the University of Michigan, Ann Arbor, where he is founding director of the Center for Hybrid Intelligence Systems (HyIntS Center), and leads the Crowds+Machines (CROMA) Lab. Walter's lab creates interactive intelligent systems that are robust enough to be used and trained in real-world settings by combining both human and machine intelligence to exceed the capabilities of either. These systems let people be more productive, and improve access to the world for people with disabilities.

Ranjitha Kumar, Ph.D., is an Assistant Professor in the Department of Computer Science and (by courtesy) the Department of Electrical and Computer Engineering at the University of Illinois at Urbana-Champaign. She runs the Data Driven Design Group, where she and her students leverage data mining and machine learning to address the central challenge of creating good user experiences: tying design decisions to desired outcomes. Ranjitha received her PhD from the Department of Computer Science at Stanford University. She was formerly the Chief Scientist at Apropose, Inc., a data-driven design company she co-founded.

Otmar Hilliges, Ph.D., is an Associate Professor of Computer Science at ETH Zürich. He currently is the head of the Institute for Intelligent Interactive Systems and leads the AIT group. His research interests are in machine perception

of human activity, including pose estimation, activity recognition and other forms of input sensing. Furthermore, he is interested in algorithms that can extract high-level concepts such as style and semantic meaning from observations of human activities and algorithms that continuously update individualized user models (based on such data). Prior to joining ETH he was a Researcher at Microsoft Research Cambridge, in the I3D group. He earned a PhD in Computer Science from LMU München, Germany. Otmar broadly publishes in top-tier HCI and ML venues including CHI, UIST, ICLR and CVPR.

### Website

Workshop website: <https://sites.google.com/view/ai4hci>

### Pre-Workshop Plans

The organizers plan to broadly advertise the workshop in a variety of communities including both HCI and AI researchers and practitioners. The organizers will do so by announcing in email via distribution lists and physically in various talk opportunities they have around the world. The organizers will also publicize the workshop over social media, such as Twitter and Facebook to gain an even wider engagement with the communities. Meanwhile, we will specifically invite top researchers and practitioners to attend the workshop, and encourage them to circulate the workshop announcement within their institutions. We will make our workshop website available upon the workshop acceptance, which will feature a Call for Participation, information about organizers, paper submission instructions and a workshop agenda once position papers are selected.

### Workshop Structure

We propose to hold the one-day workshop as part of CHI 2020 pre-conference program. The number of the attendees will be between 20 and 25 participants (including the

organizers). We will open the workshop by announcing the agenda, which is followed by a keynote given by an invited leading researcher who is working at the intersection of HCI and AI. We will then ask all the participants to give a short talk about their position paper with a brief Q&A. Participants will have the opportunity to propose topics to discuss for the second half of the workshop. We will organize a lunch event for participants to socialize. In the second half of the workshop, we will have group discussions around the topics proposed in this proposal as well as those compiled from participant votes. We will ask participants to attend a group of interest with each moderated by either a workshop organizer or a participant volunteer. We will then ask each group moderator to report back their discussion outcomes to all the participants in a debriefing session. We will close the workshop by summarizing what we have learned and soliciting thoughts for future activities.

### Post-Workshop Plans

We will compile and report the results of the workshop on the workshop's website, which might result in a survey article in HCI or AI magazines. We will seek opportunities to collaborate with participants to work on the survey, based on their position papers and further contribution to the venue. We will plan future workshops to support further conversations about these topics, fostering cross-field collaboration between HCI and AI, and disseminating best practice, resources and knowledge of these topics to both fields.

### Call For Participation

Modern approaches of Artificial Intelligence, which are data-driven and computational model centric, have a broad impact on how each field tackles its own challenges. There are increasing interests in the HCI field of using these modern AI methods to address both classic and emerging HCI

problems. While these methods offer great capacities to solve complex problems, using these methods in HCI works also pose challenges.

The goal of this workshop is to start the conversation on several fronts regarding how to effectively use these methods in our field in conjunction with traditional HCI approaches. In particular, the workshop will discuss:

- HCI topics that have been investigated by using modern AI methods and problems that are still under explored;
- Challenges in working at the intersection between AI and HCI, including the tension between the limited scale of HCI dataset and that demanded by these AI methods such as deep learning.
- Issues about how AI model-based work can make useful contribution to the HCI field, reconciling aspects of a contribution valued by different fields.
- Progress and methods for deriving analytical understandings about AI models that are relevant to HCI, rather than only using the output of the model.
- Cases and insights into how to combine guideline or heuristic-based approaches with data-driven ones.
- Tools and datasets can be shared in the community to accelerate works at the intersection of HCI and AI.

Participants should submit a position paper that is 2-4 pages long (including references) in the CHI Extended Abstracts Format that outlines their view on the workshop theme and the reasons for their interest in the topic including their previous work related to the workshop topic. Papers should be

submitted to the workshop website. We will select papers based on their relevance, quality, and diversity. Participants from both computational and design backgrounds are welcome. At least one author of each accepted position paper must attend the workshop and all participants must register for both the workshop and for at least one day of the conference. Workshop website: <https://sites.google.com/view/ai4hci>

## REFERENCES

- [1] Emre Aksan, Fabrizio Pece, and Otmar Hilliges. 2018. DeepWriting: Making Digital Ink Editable via Deep Generative Modeling. In *SIGCHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA.
- [2] Xiaojun Bi, Yang Li, and Shumin Zhai. 2013. FFitts Law: Modeling Finger Touch with Fitts' Law. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 1363–1372. DOI : <http://dx.doi.org/10.1145/2470654.2466180>
- [3] Andy Cockburn, Carl Gutwin, and Saul Greenberg. 2007. A predictive model of menu performance. In *CHI*.
- [4] Biplab Deka, Zifeng Huang, Chad Franzen, Joshua Hibschan, Daniel Afergan, Yang Li, Jeffrey Nichols, and Ranjitha Kumar. 2017. Rico: A Mobile App Dataset for Building Data-Driven Design Applications. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology (UIST '17)*. ACM, New York, NY, USA, 845–854. DOI : <http://dx.doi.org/10.1145/3126594.3126651>
- [5] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. 2009. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR09*.
- [6] Paul M. Fitts. 1954. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology* 47 6 (1954), 381–91.
- [7] Christoph Gebhardt, Brian Hecox, Bas van Opheusden, Daniel Wigdor, James Hillis, Otmar Hilliges, and Hrvoje Benko. 2019. Learning Cooperative Personalized Policies from Gaze Data. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology (UIST '19)*. ACM, New York, NY, USA, 10. DOI : <http://dx.doi.org/10.1145/3332165.3347933>
- [8] Oliver Glauser, Shihao Wu, Daniele Panozzo, Otmar Hilliges, and Olga Sorkine-Hornung. 2019. Interactive Hand Pose Estimation Using a Stretch-sensing Soft Glove. *ACM Trans. Graph.* 38, 4, Article 41 (July 2019), 15 pages. DOI : <http://dx.doi.org/10.1145/3306346.3322957>
- [9] Zhe He, Adrian Spurr, Xucong Zhang, and Otmar Hilliges. 2019. Photo-realistic Monocular Gaze Redirection using Generative Adversarial Networks. In *International Conference on Computer Vision (ICCV '19)*. IEEE.
- [10] William Edmund Hick. 1952. On the rate of gain of information.
- [11] Ranjitha Kumar, Arvind Satyanarayan, César Torres, Maxine Lim, Salman Ahmad, Scott R. Klemmer, and Jerry O. Talton. 2013. Webzeitgeist: design mining the web. In *CHI*.
- [12] Ranjitha Kumar and Kristen Vaccaro. 2017. An Experimentation Engine for Data-Driven Fashion Systems. In *AAAI Spring Symposia*.

- [13] Walter S. Lasecki. 2019. 1 On Facilitating Human-Computer Interaction via Hybrid Intelligence Systems.
- [14] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep learning. *Nature* 521, 7553 (27 5 2015), 436–444. DOI : <http://dx.doi.org/10.1038/nature14539>
- [15] Yang Li, Samy Bengio, and Gilles Bailly. 2018. Predicting Human Performance in Vertical Menu Selection Using Deep Learning. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 29, 7 pages. DOI : <http://dx.doi.org/10.1145/3173574.3173603>
- [16] Seonwook Park, Xucong Zhang, Andreas Bulling, and Otmar Hilliges. 2018. Learning to Find Eye Region Landmarks for Remote Gaze Estimation in Unconstrained Settings. In *ACM Symposium on Eye Tracking Research and Applications (ETRA) (ETRA '18)*. ACM, New York, NY, USA.
- [17] Ken Pfeuffer and Yang Li. 2018. Analysis and Modeling of Grid Performance on Touchscreen Mobile Devices. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 288, 12 pages. DOI : <http://dx.doi.org/10.1145/3173574.3173862>
- [18] Jie Song, Gábor Sörös, Fabrizio Pece, Sean Ryan Fanello, Shahram Izadi, Cem Keskin, and Otmar Hilliges. 2014. In-air Gestures Around Unmodified Mobile Devices. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology (UIST '14)*. ACM, New York, NY, USA, 319–329. DOI : <http://dx.doi.org/10.1145/2642918.2647373>
- [19] Amanda Swearngin and Yang Li. 2019. Modeling Mobile Interface Tappability Using Crowdsourcing and Deep Learning. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 75, 11 pages. DOI : <http://dx.doi.org/10.1145/3290605.3300305>
- [20] Kristen Vaccaro, Tanvi Agarwalla, Sunaya Shivakumar, and Ranjitha Kumar. 2018. Designing the Future of Personal Fashion. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 627, 11 pages. DOI : <http://dx.doi.org/10.1145/3173574.3174201>
- [21] Jacob O Wobbrock, Andrew D Wilson, and Yang Li. 2007. Gestures without libraries, toolkits or training: a \$1 recognizer for user interface prototypes. In *Proceedings of the 20th annual ACM symposium on User interface software and technology*. ACM, 159–168.