Grand Challenges for Personal Informatics and AI

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Increasing availability of personal data opened new possibilities for technologies that support individuals' reflection, increase their self-awareness, and inform their future choices. Personal informatics, chiefly concerned with investigating individuals' engagement with personal data, has become an area of active research within Human-Computer Interaction. However, more recent research has argued that personal informatics solutions often place high demands on individuals and require knowledge, skills, and time for engaging with personal data. New advances in Machine Learning (ML) and Artificial Intelligence (AI) can help to reduce the cognitive burden of personal informatics and identify meaningful trends using analytical engines. Furthermore, introducing ML and AI can enable systems that provide more direct support for action, for example through predictions and recommendations. However, there are many open questions as to the design of personal informatics technologies that incorporate ML and AI. In this workshop, we will bring together an interdisciplinary group of researchers in personal informatics, ML, and AI to outline the design space for intelligent personal informatics solutions and develop an agenda for future research in this area.

CCS CONCEPTS • Human-centered computing → Ubiquitous and mobile computing → Ubiquitous and mobile computing systems and tools

Additional Keywords and Phrases: personal informatics, artificial intelligence, AI, machine learning, self-tracking

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1 INTRODUCTION

Increasing availability of personal data due to a rise in mobile and wearable devices has opened new possibilities for technologies that support individuals' reflection, increase their self-awareness, and inform their future choices. The practice is widespread, with nearly half of Americans having tried to use technology to monitor their physical activity or diet, and nearly a quarter having tried to monitor their sleep and mental health [20]. Study and design of this technology has become an area of active research within Human-Computer Interaction, often referred to as personal informatics [14]. Research in personal informatics has risen greatly in recent years, averaging roughly 50 related publications per year in ACM venues and with over 100 publications at CHI alone in the past decade [7].

Research in personal informatics has frequently emphasized the knowledge, skills, and time burdens that technology requires to engage with personal data and achieve self-tracking goals [17],[3],[4]. Similarly, personal informatics systems that aim to support action--such as interventions for health behavior change, have not been able to adequately adapt to changes in individuals' needs and abilities (e.g., knowing to stop providing physical activity goals when a person has the flu, or when the individual might be suffering from an eating disorder), leading to user frustration, lack of trust, and sometimes even counter-productive outcomes [18]. These burdens often result in the technology being abandoned, interventions not being as useful as desired, people failing to achieve their goals, and miscoordinations between the individuals and other stakeholders in the ecosystem of their wellness [19],[12],[5],[8]. Recent advances in Machine Learning (ML) and Artificial Intelligence (AI) have the potential to help address some of these challenges and pave the way for a new generation of personal informatics technologies that reduce the cognitive burden of data analysis, and provide more robustly tailored support for action with predictions and recommendations. For example, the effort of drawing understanding out of collected data could potentially be reduced through analytical engines which identify meaningful and noteworthy trends [1]. Recent work has also suggested that predictions and personalized recommendations driven by ML and AI can help provide more direct support for acting on data [10],[6],[15]. Potentially, AI/ML approaches may able be able to identify not just what could be good times to intervene, but also contexts when tracking or reflections on one's personal data should be held back [13].

Despite such potential benefits, the involvement of AI in personal informatics systems poses significant design, interaction, and sociotechnical challenges for the HCI community to consider. Self-tracking tools often rely on small datasets from a single individual to form insights [9], which often does not align with the requirements or expectations of ML models. This limitation can be somewhat addressed by aggregating data across individuals, but doing so opens important questions around how to use population-level models to provide personalized insights, and who is often left out by these aggregations. Furthermore, recent research in ethical AI has persistently observed biases and inequities to be perpetuated when models built on population data are applied in the unique health contexts of minoritized groups

[16]. Developing and examining AI-powered personal informatics systems also requires rethinking our traditional interaction paradigms around personal informatics tools, moving beyond mobile applications to consider the value of different agents for providing recommendation, or multimodal interactions. These challenges are further mediated by the circumstances, preferences, and length of engagement expected for interacting with AI in personal informatics systems.

Given the intersecting rise of personal informatics research and AI research within the HCI community, now is an important time to have conversations about the role of AI in personal informatics. We therefore propose to conduct a workshop where we bring together experts in these respective fields to discuss and address key challenges, outline a research agenda for the future, and report back to the research community at large.

2 GRAND CHALLENGES FOR PERSONAL INFORMATICS AND AI

We will organize our workshop around grand challenges—problems that, if we can make some progress on, will significantly increase the effectiveness, usability, and value of AI algorithms in various kinds of personal informatics applications such as health interventions and sensemaking tools. Through collective discussion as an organizing committee, we have arrived at the following challenges to focus on during the workshop. We plan to further elaborate on these challenges in preparation to and during the workshop, potentially consolidating some, and adding new ones, and use these challenges to outline new directions for research.

2.1 Forms of support and interaction paradigms:

One of the main tasks of AI-powered systems is to inform human judgments, decisions, and actions. However, questions remain as to the specific forms of support that can be of value to the person(s) whose data is being collected, and how might those forms of support complement or augment existing support systems. For example, what forms of output (inferences, predictions, recommendations) are appropriate and useful in different contexts? Are there tensions between more direct support for action (predictions/recommendations) and support for self-awareness and learning, typical for personal informatics, and how can AI-powered systems support both? Correspondingly, different forms of support may require different types of interaction, including embodied agents, voice assistants, chatbots, and graphic interfaces. What forms of interaction are appropriate for AI-driven personal informatics systems? How does the utility of each interaction vary based on the form of output, personal preferences, context, goals, and length of engagement (e.g., days versus years)? What opportunities exist for multimodal interactions with AI-powered systems?

2.2 Limitations of self-tracking data in AI models:

Some of the greatest breakthroughs in ML came from models that require vast datasets (e.g., deep learning). However, these datasets are not always feasible in personal informatics where collection of personal data may be burdensome due to it often involving self-report/manual logging (e.g., diet tracking, or mood tracking). What ML approaches can help to arrive at robust inferences with sparse, individual, and/or short-term records? Furthermore, passive tracking has less burden but may result in noisy datasets and often require mapping between what is being captured (galvanic skin response, steps) and what investigators wish to capture (stress levels, physical activity). How do we create useful AI-driven interactions which effectively make these limitations more visible and intelligible to users? Are there opportunities to triangulate between passively and actively collected data to get closer to the "truth"? What ML approaches allow us to overcome the limitations of learning on the data from a single individual, while still providing personalized, relevant support? How can AI-based systems be useful before there is sufficient data to enable accurate inferences/predictions?

2.3 Representativeness of AI models:

Most AI models are trained on populations with majority identities (e.g., people in high income countries, and those tend to be younger, urban, and healthier). It is well-known that personal informatics systems are more widely-used by these majority groups, and their use often deepens or surfaces disparities around the ability to interpret complex representations of personal data, perform physical activity, have access to healthy food, and more. What social justice issues need to be considered when these AI models are implemented widely in personal informatics interventions? Would people with minority identities (racial or ethnic minorities; LGBTQIA+; older adults and kids; people with disabilities; socio-economically disadvantaged individuals) be marginalized, and if so, in what ways? What approaches to establishing models and adapting interventions should we take to mitigate these disparities?

2.4 Personalization:

Leveraging AI to personalize delivery of recommendations or advice based on PI data is a frequent topic of interest, such as in Just-In-Time Adaptive Interventions (JITAIs, [11]). Open questions remain about when or how to personalize delivery of these interventions, or whether personalization may negatively impact the intervention's adherence to population-level guidelines for health and wellbeing. For example, if the system consistently reduces physical activity goals because the user's calendar indicates that they are busy, this may lead to lower overall activity levels than if the system did not do such tailoring of support. What opportunities exist for personalization of interventions, such as their timing, form, and tone, and in what situations personalization can harm and marginalize rather than benefit users? More broadly, what are the tradeoffs of personalizing support vs. not in different contexts and across different types of PI systems? Similarly, interactive ML or machine teaching approaches can support fine-tuning and personalizing the underlying model of a person, combining personal data and explicit input from the person. What contexts would benefit from these teachable moments, and how can technology support this process? In addition, in such hybrid, human-in-the-loop systems, how do different user actions (provision of information about the current state, reactions to provided support, etc.) enhance the functioning of the algorithms contained in AI-based PI systems?

2.5 The role of the human:

One of the defining characteristics of personal informatics systems is the support for user agency: PI users typically have full control over data collection and use. However, many contemporary AI-powered solutions leave humans out of the data collection loop and often view them only as data contributors, and as receivers of inferences, predictions, and recommendations [2]. Are there opportunities to leverage the intelligence of new generations of AI-powered personal informatics systems without losing user agency, autonomy, and control? For example, what techniques can help users control not only data collection (selection of data streams and variables) but also the learning process, and transition from machine learning to machine teaching, for example through increased visibility of internal model's representations of the user? Furthermore, what is the long-term impact of increased reliance on AI-powered systems on people's self-management and self-awareness goals, which are at the heart of personal informatics systems? Finally, with the increasing popularity of AI-powered personal informatics systems in health, how do these systems impact human-human relationships in this context? For instance, what impact would recommendations, insights, plans, or procedures driven by AI systems leveraging personal informatics data have on the therapeutic alliance between a mental health patient and their clinician, or the collaborative efforts between members of the treatment team?

3 ORGANIZERS

Because of the interdisciplinarity and relevance of our topic to current conversations in the field, we intentionally opted for an interdisciplinary organizing team that is on the larger end of what's typical of a CHI workshop and that incorporates researchers with different backgrounds. While all of our organizers have some experience conducting research involving both personal informatics and AI, we have intentionally recruited organizers who span the spectrum of more personal informatics-focused work, more AI-focused work, and work at the intersection of the two disciplines. Our organizers range from early-career researchers to mid-career and well-established, spanning academia, industry, and the global community.

Lena Mamykina, PhD, is an Associate Professor at the Department of Biomedical Informatics at Columbia University. Her research focuses on ways individuals engage with AI-powered systems in the context of health and medicine. Her recent projects included incorporating personalized predictions for meal-time changes in blood glucoses levels, and a conversational agent for personalized coaching in diabetes. Her work is funded by the National Science Foundation and the National Institute of Health and spans from innovative system design to clinical trials of technological interventions for self-management of chronic diseases. She holds degrees in Computer Science (BS), Human-Centered Computing (PhD) and Biomedical Informatics (BA).

Daniel Epstein, PhD, is an Assistant Professor in Informatics at the University of California, Irvine, where he directs the Personal Informatics Everyday lab. His work examines how the design of personal tracking technology can acknowledge and account for the realities of use in everyday life. He has organized multiple successful workshops on personal informatics and related topics at CHI, CSCW, and Ubicomp, and has received multiple paper awards and honorable mentions for his work at CHI. His research has been featured in the Wall Street Journal, The Atlantic, and Consumer Reports. He holds a Ph.D. in Computer Science & Engineering from the University of Washington.

Pedja Klasnja, PhD, is an Associate Professor in the School of Information at the University of Michigan. His research focuses on the development and evaluation of technologies for health behavior change and maintenance. In recent years, he has been mostly focusing on just-in-time adaptive interventions, digital interventions that use AI algorithms to personalize intervention provision to maximize intended health outcomes and minimize user burden. In addition to developing novel interventions, he also develops methods for optimization of digital interventions and for more efficient accumulation of evidence about such systems. Dr. Klasnja's work is funded by the National Institutes of Health, with recent awards to develop and evaluate interventions for secondary prevention of cardiovascular disease, weight management, and primary prevention of cancer. He is also a lead of the methods core on a recently funded center for optimization of strategies used in initiatives to implement evidence-based clinical practice.

Donna Spruijt-Metz, MFA, PhD is a Research Professor in both Psychology and Population and Public Health Sciences at the University of Southern California. She has focused for most of her career on mobile technologies to understand health-related behaviors as well as to prevent and treat obesity and diabetes in ethnically diverse youth and families. Her main interest is in developing dynamic, ideographic models of behavior that can ultimately be used to intervene adaptively and 'just in time'. She is currently Multiple PI (with Pedja Klasnja) on the U01 (NCI) Operationalizing Behavioral Theory for mHealth: Dynamics, Context, and Personalization, on the R01 (NIDDK) Function and Emotion in Everyday Life with Type 1 Diabetes: FEEL-T1D, and on the R01 (NIDA) Cultural Stress, Stress Response, and Substance Use among Hispanic Adolescents. She is also leader of the Investigator Development Core of a newly funded center to reduce health disparities in Southern California (P50, NIMHD). She founded and co-directs the USC mHealth Collaboratory with Dr. William Swartout, a leader in Artificial Intelligence.

Jochen Meyer, PhD, is director of the Health department at OFFIS - Institute for Information Technology in Oldenburg, Germany, where he is responsible for about 30 researchers working in regional, national and international projects. His research areas include technologies for wellbeing and prevention, ambient assisted living, and personal use of multimedia data, with a particular interest on long-term tracking in daily life. He is an active member of the research community, has amongst others conducted numerous workshops at CHI and other venues, was General Chair of IEEE ICHI 2020, and was AC of CHI 2019, 2020 and 2022.He holds a diploma and a PhD in Informatics from the University of Oldenburg.

Mary Czerwinski, PhD is a Partner Researcher and Research Manager at Microsoft Research. Mary's research focuses primarily on information worker task management, health and wellness. Her background is in visual attention and multitasking. She holds a PhD in Cognitive Psychology from Indiana University in Bloomington. Mary was awarded the ACM SIGCHI Lifetime Service Award, was inducted into the CHI Academy, and became a Fellow of the ACM in 2016. She also received the Distinguished Alumni award from Indiana University's Brain and Psychological Sciences department in 2014 and from the College of Arts and Sciences from Indiana U. in February, 2018. Mary became a Fellow of the American Psychological Science association in 2018 and was recognized as an EAI (European Alliance for Innovation) Fellow in 2019.

Tim Althoff, PhD, is an Assistant Professor in the Paul G. Allen School of Computer Science & Engineering at the University of Washington. His research advances computational methods that leverage large-scale behavioral data to extract actionable insights about our lives, health and happiness through combining techniques from data science, social network analysis, and natural language processing. Tim holds Ph.D. and M.S. degrees from Stanford University and M.S. and B.S. degrees from the University of Kaiserslautern, Germany. He has received several fellowships and awards including the SAP Stanford Graduate Fellowship, Fulbright scholarship, German Academic Exchange Service scholarship, the German National Merit Foundation scholarship, a Best Paper Award by the International Medical Informatics Association, the WWW 2021 Best Paper Award, two ICWSM 2021 Best Paper Awards, and the SIGKDD Dissertation Award 2019. Tim's research has been covered internationally by news outlets including BBC, CNN, The Economist, The Wall Street Journal, and The New York Times.

Eun Kyoung Choe, PhD, is an Associate Professor in the College of Information Studies at the University of Maryland, College Park. Her research bridges the fields of Human-Computer Interaction (HCI), Health Informatics, and Ubiquitous Computing. With an overarching goal of empowering individuals, her research centers on examining major challenges people face in leveraging personal data, such as personal data collection and exploration. Her work has been funded by the National Science Foundation, National Institutes of Health, and Microsoft Research. She has been serving on the editorial boards of PACM IMWUT and Foundations and Trends in Human-Computer Interaction. She received her PhD in Information Science from University of Washington.

Munmun De Choudhury, PhD, is an Associate Professor of Interactive Computing at Georgia Tech. Dr. De Choudhury is best known for laying the foundation of a line of research that develops computational techniques to responsibly and ethically employ social media in understanding and improving our mental health. Dr. De Choudhury has been recognized with the 2021 ACM-W Rising Star Award, 2019 Complex Systems Society – Junior Scientific Award, numerous best paper and honorable mention awards from the ACM and AAAI, and features and coverage in popular press like the New York Times, the NPR, and the BBC.

Brian Lim, PhD, is an Assistant Professor in the Department of Computer Science at the National University of Singapore (NUS). He leads the NUS Ubicomp Lab focusing on research on ubiquitous computing and explainable artificial intelligence for healthcare, wellness and smart cities. His research explores how to improve the usability of explainable AI by modeling human factors, and applying AI to improve clinical decision making and user engagement towards healthier lifestyles. He has been serving on the editorial board of PACM IMWUT and program committees for CHI and AAAI. He received a B.S. in engineering physics from Cornell University and a Ph.D. in human-computer interaction from Carnegie Mellon University.

4 LINK TO WEBSITE

We have created a draft of our website here, which we will continue to update as the event gets closer: https://piandaichi2022.weebly.com/

5 PRE-WORKSHOP PLANS

We will solicit workshop position papers from researchers around the grand challenges described above, asking each paper to promote a vision or strategy for addressing one of these challenges. We therefore expect position papers to depict an aspirational goal or strategy, or outline some of the difficulties that we as designers and researchers might face when trying to address the grand challenges. Although authors might draw on their empirical work designing, studying, or evaluating personal informatics systems with AI, we expect position papers to primarily discuss the implications of that work for the grand challenges outlined.

We will limit workshop submissions to no more than 3 pages (excluding references) in ACM's template, and they will be submittable to an email address created for the workshop. Each submission will be reviewed by at least one workshop organizer and be given some light feedback. Should the workshop receive more submissions than we are able to accept, we will have some discussion among the organizers around which position papers are most relevant to the workshop theme and topics.

We will advertise the workshop broadly in ACM SIGCHI-affiliated groups on social media and messaging platforms, such as the CHI-meta Facebook group and the SIGCHI Discord channel, as well as our own social networks (e.g., Twitter feeds). We will additionally utilize the existing contacts of the organizers to directly reach out to other researchers conducting work on personal informatics and AI.

6 WORKSHOP STRUCTURE

To accommodate the goal of conducting a large workshop and potential COVID-19 related travel impacts on the international organizing committee, we plan for this 1-day workshop to be **synchronous** and **virtual-only**. We intend to accept submissions from 20-25 participants. If supported by the conference, we would be open to allowing for up to 30 CHI attendees to register for the workshop without presenting a position paper.

The workshop will start on the conference platform with a brief introduction from the organizers. The main structure of the workshop will include lightning panels and small group discussions organized around the grand challenges. We will use the five grand challenges outlined above as a starting point and to advertise the workshop. We will refine the list of the grand challenges based on submissions and will select three grand challenges that received most attention and interest from the participants. Each panel will include brief presentations (no more than five minutes) from researchers whose position papers aligned with the specific challenge. Each panel will be followed by break-out group discussions;

each group will contain about five attendees, including a mix of researchers in personal informatics and AI and will include at least one of the co-organizers who will serve as a moderator and a scribe. Each group will be asked to generate several promising directions for future research to address the specific grand challenge. Each group will be asked to report back on their ideas, followed by a general discussion of trends across groups. To promote better discussion and minimize fatigue, we may adjust the exact timing and ordering of the sessions should we get more or fewer submissions related to a particular grand challenge.

This formal part of the workshop will be followed by an informal, optional session on Gather.town. We will provide some unstructured socialization time to allow participants and presenters to mingle, network, and ask follow-up questions from the panel sessions.

The tentative agenda we plan to follow can be found below. All times are in PST. Given the distributed nature of the workshop, we have attempted to pick continuous blocks of time that will allow researchers throughout the globe to participate. We recognize the unfortunate reality of virtual conference events where participants in certain time zones might be negatively affected and will work with submitters and attendees to modify our timing and support asynchronous participation as needed.

8:00am - 8:15am Welcome and organizer introduction on conference platform
8:15am - 8:30am Grand Challenge #1 panel
8:30am - 9:00am Grand Challenge #1 break-out discussions
9:00am - 9:15am Grand Challenge #1 report back
9:15am - 9:30am BREAK
9:30am - 9:45am Grand Challenge #2 panel
9:45am - 10:15am Grand Challenge #2 break-out discussions
10:15am - 10:30am Grand Challenge #2 report back
10:30am - 10:45am BREAK
10:45am - 11:00am Grand Challenge #3 panel
11:00am - 11:30am Grand Challenge #3 break-out discussions
11:30am - 11:45am Grand Challenge #3 report back
11:45am - 12:00pm Summary and next steps
12:00am - 1:00pm Informal social gathering on gather.town

7 TECHNICAL PLANS

We expect that our workshop can be primarily conducted via a videoconferencing service (e.g., a Zoom created by one of the organizers or a conference-provided platform) and a Gather.town link. The organizing team has extensive experience using these platforms for organizing virtual events, such as a Health-related social event for CHI 2021 on Gather.town and numerous workshops on Zoom. Student volunteer support around presentation logistics (e.g., enabling screen-sharing for speakers and panel formation) would be desirable, but we do not expect specialized technical support needs.

To support asynchronous engagement and participation, we plan to record (with consent) the presentations in the panel sessions for later viewing, and will encourage the panelists to place any slides or other materials in a shared repository (e.g., a Google Drive folder). We will also create notes documents for each of the break-out discussion groups ahead of the workshop, making them accessible to all interested attendees. Although those documents will be populated during synchronous discussion and referred to during the report back sessions, leaving those documents available will help support people who may encounter technical issues during the workshop or may wish to engage with people's thoughts further.

8 POST-WORKSHOP PLANS

We also hope to cultivate a network among scholars and practitioners with different areas of experience, to foster collaboration, and to raise collective awareness of the questions and topics we are tackling. By bringing together organizers across academia and industry, with a diverse history of research in personal informatics and AI, we offer a wide range of past experience of related work and varied networks from which to recruit workshop attendees. As a final outcome, we will summarize the discussions and disseminate our findings to the broader community, e.g., through an ACM Interactions or longer survey of the field, a special issue of a journal in an HCI venue (e.g., ToCHI), and a white paper for funding agencies.

9 CALL FOR PARTICIPATION (MAX 250 WORDS)

New advances in Machine Learning (ML) and Artificial Intelligence (AI) technologies have the opportunity to leverage Personal Informatics (PI) data to support individuals' learning, awareness, and action toward important goals. However, design of AI-based PI systems also presents design and sociotechnical challenges for HCI to consider. In this synchronous, virtual workshop at CHI 2022, we aim to bring together researchers in AI, Personal Informatics, and the intersection to discuss how we can make progress on a set of grand challenges in this field. Interested participants should submit a maximum 3-page position paper to [email address TBD] which outlines some strategies for or difficulties with addressing one of the grand challenges we have outlined: (1) identifying useful and impactful forms of support and paradigms for interacting with AI-powered personal informatics systems, (2) addressing limitations of self-tracking data for using AI models (3) ensuring representativeness of AI models across the population, (4) balancing costs and tradeoffs of AI-driven personalization of recommendation or advice based on personal informatics data, and (5) need to support human agency and connection when interacting with AI-infused personal informatics systems. Accepted position papers will be posted on our workshop website (https://piandaichi2022.weebly.com/) for the public. At least one author of accepted position papers must register to attend the workshop.

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