Ubiquitous Computing in Action: Infrastructure to Support Sensing and Mental Health Research in Practice

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Abstract

Ubiquitous computing technologies have been developed to identify and intervene on mental health symptoms, but these technologies have limited uptake in clinical care. Recent work in human-computer interaction (HCI) and digital mental health has demonstrated opportunities to conduct research in practice (i.e. in the context of care) that better identifies opportunities for technologies to meet current care needs. In this work, I propose an instantiation of research in practice, specifically to build sociotechnical infrastructure that enables ubiquitous computing research in the context of mental healthcare. Specifically, this infrastructure creates opportunities for human-centered design to study actions with ubiquitous technologies in care, as well as data collection to design, build, and evaluate interventions with these technologies in clinical settings. Through this infrastructure, I aim to align computing research with specific clinical needs, and improve the uptake of ubiquitous technologies in care and patient outcomes.

CCS Concepts

• **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**; **Empirical studies in HCI**; • **Computing methodologies** → *Machine learning*; • **Applied computing** → Health informatics.

Keywords

passive sensing, mHealth, behavioral health, mental health, clinical decision support, user-centered design, human-computer interaction

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1 Problem Statement

Almost 15 years of ubiquitous computing research has focused on designing technologies to support the early identification of and intervention on symptoms of mental illness. Researchers have identified behavioral signals in smartphone [63, 65] and wearable data [6] associated with mental health and well-being, and have leveraged these signals in interventions designed for self-tracking [18, 23] and behavior change [32]. Yet, despite these technical advancements, recent work has noted the limited progress [7, 8] in adoption and use of ubiquitous technologies in mental healthcare. This limited uptake calls for human-centered work to understand challenges towards adoption, as well as the design of technologies that better fit the needs and workflows of end users, including patients and clinicians, involved in mental health service delivery.

My work sits at the intersection of ubiquitous computing, human-centered design, and digital mental health, and I look to design ubiquitous computing technologies that enable clinical actions in mental healthcare and improve patient outcomes. In my future work, I wish to bridge the gap between research and impact by studying actions with data from ubiquitous computing technologies that improve patient care. Towards this end, I propose sociotechnical infrastructure to study ubiquitous technologies in the context of care, by using human-centered approaches to identify clinical needs that can be solved with ubiquitous computing, and then designing, building, and evaluating interventions with ubiquitous technologies that solve care challenges.

2 Related Work

2.1 Ubiquitous Computing and Mental Health

Research in ubiquitous computing and mental health has enabled both sensing and intervention technologies. From a sensing perspective, ubiquitous computing researchers have designed algorithms and systems to extract data from mobile sensing technologies – including smartphones and wearable devices – to identify behaviors related to mental health and well-being [35, 62]. This formative work motivated research to detect symptoms of mental illness with mobile sensing technologies and machine learning, including symptoms of schizophrenia [3, 64], bipolar disorder [20], depression [6, 65], and anxiety [30]. More recent work shows that mobile sensing-mental health detection tools have poor generalization accuracy in more heterogeneous populations [4, 38, 66], simultaneously suggesting that machine learning models personalized to subsections of the population may improve generalizability [56, 60], but that personalization may be difficult to implement in practice [43]. These findings suggest identifying research opportunities for mobile sensing technologies in care that are not predicated on high correlations between sensing data and symptoms.

From an intervention perspective, researchers have designed interfaces that help data subjects visualize and reflect on sensor data towards accomplishing specific health goals. For example, *personal informatics* research has focused on how patients and providers can collaborate with sensor data towards shared goals [15, 42], and data can be visualized by patients to promote health-behaviors [23, 41]. In addition, researchers have developed automated systems that deliver *just-in-time adaptive interventions* (JITAIs), where a predetermined suite of interventions are delivered when an individual is most receptive to participate [40, 49]. These technologies have focused specifically on how sensor data can enable reflection and action as adjuncts to care, focused primarily on actions taken by patients as data subjects. Recent work has also studied how sensing data can support clinical decision making by tracking patient participation in therapeutic exercises [19]. I look to build upon this existing work to understand how sensor and clinical data can be embedded in care to enable specific clinical actions that improve patient outcomes.

2.2 Infrastructure for Research in Practice

Apart from designing novel technologies, scientists often look to repurpose data and infrastructure from real-world settings to conduct research. For example, health informatics researchers often repurpose electronic health records for novel biological discovery [47, 55, 67], or analyze insurance claims to identify patterns of healthcare utilization [10, 11]. Researchers in computational social science have also scraped public social media data to study online discourse around health [36, 37]. In these examples, infrastructure intended for some real-world practice (eg, delivering and paying for healthcare, online communication) is reused for scientific inquiry.

A line of human-computer interaction (HCI) research has grappled with the ethics of conducting sociotechnical research in practice. For example, researchers in digital safety and security have analyzed methods to conduct research within a clinic assisting survivors of intimate partner violence experiencing tech-mediated harms [22, 59]. Recent work has analyzed data subjects' – specifically victims who come to the clinic for care – perspectives on repurposing data collected in practice for research, highlighting how data subject participation can improve research benefits and reduce harms [58], echoing methods of participation such as *action research* [26]. Simultaneously, data subjects should not be overburdened through participation, and studies suggest processes of reflection to confirm that conducted research is rooted in subjects' needs [48]. Observational methods, such as ethnography, offer methods to study technology users in situ with varied levels of participation, though the act of conducting research may affect users' environment and impact study findings [24, 31]. In this work, I look to instantiate and conduct sociotechnical research in practice motivated by the needs of data subjects (eg, patients) and data users (eg, patients and clinicians) in mental healthcare, through both observation and participatory work.

2.3 Digital Mental Health Research in Practice

Researchers in digital mental health have explored ways to instantiate research in practice through building *digital clinics*, where digital platforms are integrated into clinical workflows to both conduct research and deliver care [50]. These platforms collect *patient generated health data*, including mobile sensing data and self-reported mental health symptoms, which can be integrated into existing care platforms and viewed by patients and care providers [61]. Specific care staff, called *digital navigators*, support technology integration in care [46]. Digital navigators work with care teams to bring technology into care via mobile applications that augment data collection and deliver interventions [16].

Implementations of digital clinics with mobile sensor data have centered on *digital phenotyping*, where sensor data is used to learn about disease [27] and uncover emerging symptoms [28]. Aligning digital phenotyping applications within existing clinical workflows is difficult [16]. Mental health clinicians struggle to use traditional mental health data in care [21] despite evidence suggesting routine symptom measurement improves outcomes [9], and adding mobile sensing data to care faces similar resistance [44]. This calls for participatory and collaborative approaches with practicing clinicians and their patients to both design and implement sensing technologies in care, meet current clinical needs, and increase the effectiveness of ubiquitous technologies in care.

In my dissertation work, I presented the idea of **actionable sensing** to unify research studying actions users can take with sensing data in clinical care. Actionable sensing research is not solely focused on phenotyping, but is more broadly focused on how sensing can support clinicians' understanding of their patients to drive treatment actions and improve outcomes. The motivation for studying actionable sensing stems from design exercises with clinicians and literature describing how mobile sensing data – on behavior and physiology – and self-reported mental health symptoms offer complementary perspectives in treatment [5, 44], contesting that these data types are synonymous, as assumed by the phenotyping paradigm [51, 54]. Continuing to center human-centered design within the building and implementation of ubiquitous technologies may be an essential and pragmatic approach to refine these technologies and meet clinical needs [39].

Inspired by these ideas, I propose infrastructure to study actionable sensing in the context of clinical mental healthcare. This infrastructure will offer a novel instantiation of research in practice, where human-centered design is used to study patient care and identify care challenges, and then novel computing solutions are built and integrated within interventions to solve these challenges. In the following sections, I provide an example of how such infrastructure could be built and enable ubiquitous computing research in clinical mental healthcare.

3 Methodology

I plan to design and build infrastructure to enable actionable sensing research in mental healthcare. Example infrastructure is summarized in Figure 1. This infrastructure is intended to (1) bring mobile and clinical data into care and (2) allow for research in practice with novel computational tools that provide this data.

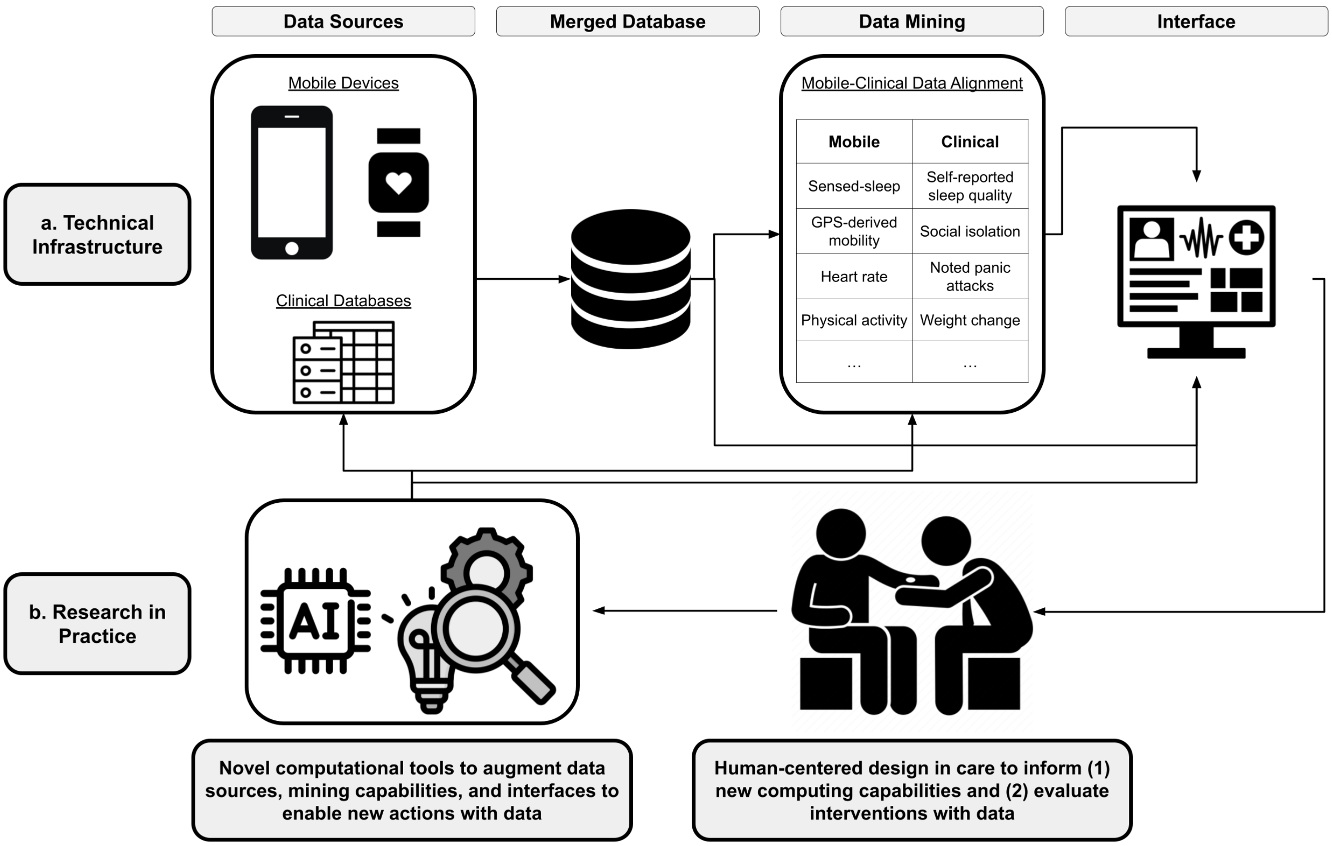

Figure 1: An example technical of (a) technical infrastructure (Section 3.1) to enable (b) actionable sensing research in practice resulting in refined data sources, mining capabilities, and interfaces (Section 3.2).

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3.1 Technical Infrastructure Design

First, I aim to collaborate with clinical and health informatics researchers as well as conduct design work with end users (eg, patients, clinicians, and health systems administrators) to design and build technical infrastructure that enables actionable sensing (Figure 1a). Towards my dissertation, I conducted formative work [5, 44] with mental health clinicians to understand how mobile sensing data can be used in the context of care. Specifically, my findings detailed how complementary mobile sensing (eg, sensed-behavior, physiology) and clinical mental health (eg, symptom scales) data can enable specific actions in care. In addition, these findings reveal opportunities to build data mining tools that align mobile and clinical data in the context of care – for example, a tool that surfaces sensed-behavioral data on sleep when patients report they are experiencing insomnia. This technical infrastructure will need to support the integration of clinical and mobile data sources, with an interface that allows clinicians and their patients to navigate data, supported by data mining tools to identify relevant data for care.

Technical infrastructure will initially be built to enable the viewing and interaction with a minimum set of mobile and clinical data most relevant for care, which can be augmented. Initial data types will be chosen in consultation with clinical collaborators and the research, prioritizing data relevant to specific clinical populations we choose to study (eg, individuals living with major depressive disorder and comorbid generalized anxiety disorder), as well as data ubiquity. For example, researchers have identified associations between GPS-derived mobility, phone usage data and symptoms of major depressive disorder [4, 53]. These mobile data types can be collected on smartphones, which are owned by a greater share of the population than wearable devices [52]. Prioritizing ubiquitous data will increase our ability to conduct research on diverse populations, whereas prioritizing data only available on newer, wearable devices may increase the "digital divide" in care [14].

Finally, I will create tools that mine available data and interfaces that display mined data outputs. For example, phone usage data can estimate sleep duration [1], which can be aligned with self-reported sleep changes (a symptom of major depressive disorder [34]) over time and visualized on interfaces used in care. Visualization preferences can vary across patients and clinicians [12], and thus interfaces will need to be flexible, with options to display data using different types of visualization. This technical infrastructure will provide the foundation to conduct research in care.

3.2 Research in Practice

Similar to [59, 61], I aim for this technical infrastructure to facilitate sociotechnical research in practice – to identify opportunities and barriers for novel interventions, sensing technologies, data mining techniques, and interfaces within care. Examples of research in practice to improve care delivery can be found in Figure 1b. First, human-centered design research through observation and interviews [2, 44, 45] can identify clinical needs not served by existing technical infrastructure, motivating computing research. In addition, this work can identify specific actions with data in care, which can be formalized into interventions for evaluation.

Identified needs will inform computational research, which can augment technical infrastructure. For example, clinicians may require new types of sensing tools that enable actions in care, for example, passive sensing tools that enable clinicians to monitor when patients refill prescriptions, or AI tools that enable the identification and visualization of context-specific data (eg, sleep data for patients experiencing insomnia). Computing research will look to design and evaluate methods that enable these new capabilities across existing or with new data. Validated methods can then be integrated into the technical infrastructure, by updating the data sources, mining algorithms, and interfaces.

Critical towards to this work are sustainable funding streams to recruit and maintain mental health clinicians (eg, psychotherapists) that deliver care, as well as technologists (eg, software developers) to build and sustain the technical infrastructure. I plan to work with clinical collaborators and the community at my current or future home institution to pursue funding opportunities to maintain and sustain both this research and the care infrastructure. In addition, I will work with the UbiComp community to identify methods, ideas, and best practices towards enabling clinical-technical collaborations that allow for computational research in care.

4 Evaluation

Infrastructure evaluation will focus on (1) technical evaluation of new components, (2) the usability of the infrastructure, and (3) outcomes within sensing-enabled care. For (1), I will evaluate the accuracy of new sensing or data mining capabilities. For example, a new capability to passively sense when patients refill their prescriptions will be evaluated for its accuracy against a ground truth (eg, self-report, contextualized within care to affirm accuracy). Given sensing can be imperfect – behaviors relevant for mental health can be heterogeneous and contextual [4, 38] – technical evaluation may prioritize (2) usability, creating accurate-enough sensing tools, whose outputs can be displayed within interfaces that enable actions in care. Usability evaluation will be adapted from common scales for technology acceptance and perceived usefulness [13, 17]. Finally, (3) interventions will be evaluated against care outcomes. These outcomes may be condition-specific – for example, reduced depression symptoms measured using common symptom scales [34] – or more general, focused on improvements in clinician-patient working alliance [25] or health-behaviors often used as treatment targets and outcomes in behavioral interventions [29, 33, 57]. Apart from technical and clinical evaluation, continued sociotechnical work will explore the ethical challenges of enabling actionable sensing in care, for example, to ensure that data sharing adheres to patients' and clinicians' specific privacy preferences [42, 44].

5 Contribution

Actionable sensing research requires infrastructure to both identify clinical needs, and build and evaluate technology that meets these needs and enables actions to improve care outcomes. In my future work, I plan to contribute such an infrastructure that enables research on ubiquitous technologies in the context of mental healthcare in practice. This work extends existing research in (1) ubiquitous computing to build sensing technologies that identify behaviors associated with mental health [6, 63], but focuses on actions with sensing technologies in care; (2) human-computer interaction as an instantiation of research in practice on care infrastructures [59], focused on the context of clinical mental healthcare; and (3) digital mental health on "digital clinics" [16, 50], but prioritizes human-centered design and augmenting the human aspects of care with technology, instead of centering a digital platform or phenotyping as the intervention. Building and funding this infrastructure will enable ubiquitous computing research aligned with current and evolving clinical needs, to create and test innovative and ethical methods that improve care outcomes.

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