Designing Therapeutic Care Experiences with AI in Mind

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Abstract

Designing systems and services with AI functionality as part of a care experience presents a range of challenges and opportunities. Limitations with sparse or missing data can make algorithmic training difficult, while the opaqueness of some black box methods muddies the process of interpreting outcomes. Human expertise and knowledge need to be carefully integrated at appropriate stages to inform both the AI approach and the fulfillment of the overall care cycle. Tackling this complex problem space requires a multidimensional and multi-stage approach integrating technical, social, medical, design and HCI knowledge. In this presentation, we use our own work creating therapeutic AI systems for cognitive and physical training to examine six key system design challenges.

Introduction

Over the next decade, artificial intelligent machines are expected to achieve unprecedented awareness and understanding of people (Stone 2016). While the timetable and full extent of these expectations may vary (Brooks 2017), as designers, we are clearly at an important juncture in terms of grappling with AI as an increasingly significant form of design material (Holmquist 2017). In recent years, we have engaged with this material within the context of designing and deploying therapeutic systems for cognitive and physical wellness and healing. Our work is focused less on making machines that care or do caring tasks, and more on conceptualizing and orienting the entire care experience from the person's point of view - with AI in mind.

Building on this approach and our experience working within mental health and rehabilitation contexts, we propose a number of issues that we believe are important for AI wrangling designers to consider and address. We review two cases of our work in related health care domains, highlighting incidents and issues encountered therein, and derive an initial set of questions to further develop in discussion and commentary from diverse symposium participants.

Design Cases

Interactive Neurorehabilitation for Stroke

Stroke is a leading cause of serious long-term disability in the United States and the most common neurological disorder worldwide (Benjamin 2017). While physical therapy training has demonstrated increased likelihood of recovery (Krakauer 2005), the realization of such therapy in the clinic over long periods of time is difficult for multiple reasons including availability of facilities and experts, financial cost, and the intense patient effort required (multiple times a week for several years). In response, home based, patient administered approaches have emerged as a potential viable solution, which can be effective in conjunction with therapy in the clinic or even as the primary mode of therapy (Anderson 2002).

Developing automated or semi-automated healthcare systems for unsupervised use in the home presents multiple personal, technical, and design challenges (Baran 2015). Primary issues include patient non-compliance and adherence; reproducing a supervised therapist experience without the therapist present; and system constraints, including system size, system complexity and robustness, and home privacy intrusion. In response, we are currently developing the HOMER system, which uses custom designed therapy objects, a combined computer vision and machine learning approach, and an interactive tablet interface to administer an adaptive training protocol (Kelliher 2017).

For our system to work, we need to be able to accurately measure and assess patient movement quality. In addition to the fact that there is little readily available patient data to train our system on, there is also a more fundamental problem in that there is lack of consensus among physical therapists regarding the standardized, quantitative evaluation of movement quality components and the influence of such components on overall functional ability (Levin 2009). In practice, therapists typically select which components to focus on based on their individual experience and training, rather than a standardized ontology of component level labels for movement quality (Wolf 2001). These factors combine to make it very challenging for a technological rehabilitation system (whether supervised or unsupervised) to reproduce both a complex therapy experience and a reliable approach for movement quality assessment. From a design perspective, it is also vital that our system be accepted by the patient and/or the caregiver, meaning we need it to occupy a small physical footprint, be straightforward to use and maintain, provide accurate and helpful feedback, and above all, to assist in motivating the patient to adhere to the training schedule and protocol. In our presentation, we will share insights gained from our ongoing work including tradeoffs with simplified classification approaches, development of an adaptive "problem-solving" training protocol, and efforts to collect sufficient patient data to create a therapist labeled dataset for further training.

Digital Mental Health from Words to Neurons

Functional brain imaging has been useful in mapping the neural circuitry of psychiatric disorders, and promises a new understanding of the underlying neural mechanisms of psychotherapy with implications for identifying the most effective treatment for an individual (Linden 2006). Drawing on this research and an analogy to optogenetics, the controlled use of light to activate specific neurons, we speculated about creating an AI that could tailor talk therapy sessions by identifying the most effective therapeutic techniques for an individual's experiential and neural response (Barry 2009). In our wildest imaginations we envisioned that an open source collection of therapeutic techniques could also help the psychiatric community track biological evidence and patient preferences for or against any given therapeutic technique.

We built a prototype as a theoretical way to explore the idea of using machine learning to create the most efficacious therapy session for an individual. The AI system first asked the mock patient questions about their communication preferences and anxiety levels. Then, it delivered a tailored therapy session as sequential units of therapeutic techniques delivered in audio. The therapeutic units guided the patient to reflect on behaviors or learn new techniques for anxiety reduction. The system measured the anxiety levels of the mock patients after each unit of therapy and the AI adjusted the session to optimize for content that reduced anxiety. We did not incorporate brain imaging into this speculative design exploration. We did engage in discussions with developers, designers, and mock patients about the possible implications of feedback loops between patients, AI, fMRI, and a therapist working in concert to treat psychiatric disorders.

During debriefing discussions with 32 mock patients, they considered the AI helpful overall and completed their session with lower levels of anxiety than when they began. The few that had rising anxiety cited cognitive overload of the therapeutic techniques or were annoyed by the voice of the computerized therapist. Some mock patients were intrigued by the idea of an AI therapist being more "neutral" than a human one, and of a real-time feedback system that responded to their emotions. Others identified the possibility of disagreements between what a person, the AI, and the therapist might consider the "best" set of therapeutic techniques. Ethical issues about trusting the intention of an AI system and concerns about altering brain activity through an intervention were expressed.

Design issues emerged through use of our speculative prototype that call out the tensions between biological health, the lived experience, and what it means to be understood by a therapist, whether AI or human. We advocate that speculative design be used as a method for generating possibilities and identifying risks for AIs as participants in therapeutic treatments, especially to help ensure that AIs are well designed to meet the needs of patients before they are introduced into care experiences.

Design Questions

In reflecting on our design cases we identified six key questions for designers to consider as AIs grow in their complexity and capability. In exploring these questions, as a design community, we can observe how AIs understand and respect the person's point of view.

How does human behavior, captured and analyzed by AIs, influence care opportunities?

How, or should, humans and AIs reach consensus on interpretations of data (when sometimes even humans can't agree)?

How is personalization redefined and designed in an era of big data, missing data, and sparse data?

How should we design for autonomous, semi-autonomous, and human-in-the loop systems?

How should AIs be designed as trusted members of care teams?

How can design help identify and address ethical issues that emerge when AIs are involved in care?

We hope to gain insights from hearing the diverse experiences of symposium participants in response to these questions and other event provocations. This will ultimately help better equip and prepare us to design productively and mindfully with the material of AI.

Author Bios

Aisling Kelliher is an associate professor of Computer Science at Virginia Tech, with joint appointments in the School of Visual Arts and the Institute for Creativity, Arts, and Technology. Aisling co-leads the Interactive Neurorehabilitation Lab at VT, where she works with an interdisciplinary team of designers, physiotherapists, computer scientists and engineers developing light-weight, cost-effective systems for conducting semi-supervised stroke rehabilitation in the home. She is also a Co-PI in the newly formed Synergistic Musculoskeletal Adaptive Research and Technology Lab (SMART Lab), a joint initiative between the Virginia Tech Carillion School of Medicine and Carilion Clinics. The SMART Lab will investigate the impact that pain, disability, and pathology have on individuals across the lifespan through the design and development of prevention and post-injury intervention programs and systems.

Barbara Barry is the Design Strategist for the Mayo Clinic Center for Innovation and an Assistant Professor in the Mayo Clinic School of Medicine. She is an interdisciplinary research scientist who uses applied anthropology and computer science to fuel innovation in industry, public and humanitarian sectors. She has led in-depth human-centered design projects for Mayo Clinic to improve the health of young adults and co-designed patient-centered care models for emerging markets. Prior to joining Mayo Clinic, she worked with neuroscientists and psychiatrists to develop personalized digital mental health apps and led UN funded programs to understand how technology can scale education and health care interventions to help children displaced by conflict and natural disasters. Barry has a Ph.D. and M.S. from Massachusetts Institute of Technology and a B.F.A. from Massachusetts College of Art and Design.

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