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. Based on our work creating therapeutic AI systems for cognitive and physical training, we propose six key system design challenges for consideration.

Introduction

Over the next decade, artificial intelligent technologies 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 mental 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. This means considering the diversity of human actors involved in creating and experiencing AI health systems, including system designers, patients, doctors, caregivers, and family members. It also involves consideration of the perceived impact of AI systems; physically, socially, and personally.

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 for consideration when designing with AI in mind.

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 or lightly supervised use in the home presents multiple personal, technical, and design challenges (Baran 2015). Primary issues include patient adherence; recreating a supervised therapist experience without the therapist present; and system constraints, including system size, system complexity and robustness, and home privacy intrusion. While automated therapy in the home is a future end-goal for AI based systems, for now, semi-automated approaches are currently most appropriate, whereby the therapist visit occasionally in person or by video conference to evaluate patient progress and evolve the therapy protocol. In response to these challenges and realistic constraints, 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 semi-automatically and accurately measure and assess patient movement quality while they are engaged in therapy activities in the home. However, developing computational agents to assist with this need is hampered by two significant factors. First, there is little readily available patient data to train a system, while second and more fundamentally, there is a 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 and collective experience and training, rather than a standardized ontology of component level labels for movement quality (Wolf 2001). These two 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 the system needs 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. Our light weight tabletop system consists of a custom fit mat, 6 customized therapy artifacts and their container, a table mounted depth camera and mini-computer module, and a tablet device with a custom web application (see Fig 1.). This system can easily fit temporarily or semi-permanently on a kitchen table or spare room desk, and is designed for straightforward assembly, power charging, and data download. The feedback approach can be adapted to the abilities and progress of the patient (e.g. more lenient for moderately impaired or when the patient is fatigued).

The form and function of the objects in our system requires design consideration of the inter-relationships between the perceived affordances of the objects, the goals of the therapy protocol, the ability of the computational components of the system to capture the participant activity, and the desired therapy outcome with respect to everyday life activities. As such, the set of objects in our system (see Fig. 1b) are designed to support cross-mapping, problem solving, and generalizable activity strategies through their open-ended affordances, combinatorial possibilities, and perceived correlation with diverse artifacts of daily living (e.g. pushing a button, using an iron, writing with a pen, turning a key etc.)

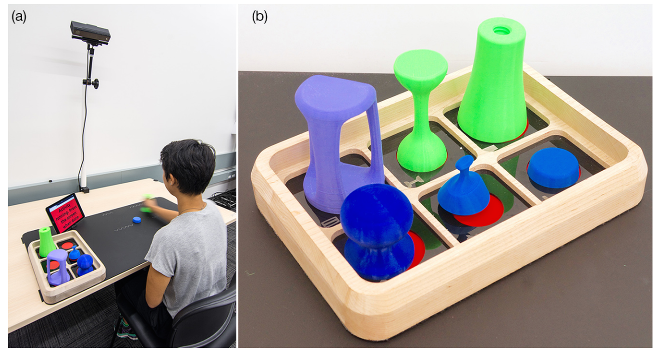

Figure 1. a) The interactive stroke rehabilitation system including mat, objects, tablet and mounted camera; b) set of 6 3D printed therapy objects

Creating functional and compelling interactive home based therapeutic systems requires a participatory and iterative design approach. Introducing sensing and control technologies (e.g. cameras and wearable sensors) into the home necessitates direct conversations between designers and home dwellers as to the nature of the data captured, access to that information, and transparency about how the AI components of the system are trained to potentially interpret it. In addition, the strength of the system is in the potential for knowledge and growth in both the human and computational agents as the system is tried out, refined, and improved based on the quality and subsequent analysis of the quantitative and qualitative data collected.

Digital Mental Health Futures

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 learning 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 an initial prototype and ran an exploratory study to examine the idea of using machine learning to create the most efficacious therapy session for an individual. The AI "therapist" followed a standardized therapeutic protocol. First, it surveyed study participant communication preferences and anxiety levels. Then, it assembled and delivered a tailored therapy session as sequential units of therapeutic techniques delivered via audio. The therapeutic units guided the participant to reflect on anxiety reinforcing behaviors and learn new techniques for anxiety reduction. The AI measured participant anxiety levels after each unit of therapy and then optimized the session for content that reduced anxiety. We did not incorporate brain imaging into this speculative design exploration. We did engage in discussions with mental health professionals, developers, designers, and study participants 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 study participants, 29 considered the AI helpful overall and completed their session with lower levels of anxiety than when they began. The three participants with rising anxiety cited cognitive overload of therapeutic techniques or were annoyed by the voice of the AI therapist. Some participants were intrigued by the idea of an AI therapist being more "neutral" than a human one and by a real-time feedback system that responded to their emotions. Others identified possible divergence between what a patient, the AI, and a therapist might consider the "best" set of therapeutic techniques. Mental health professionals questioned the algorithm responding to anxiety interval measures because an immediate rise in anxiety may mean a therapeutic technique is uncomfortable but not necessarily ineffective. Ethical issues about trusting AI system intentions and concerns about AI monitoring of mental health and brain activity were expressed.

Design issues emerged through use of our speculative prototype that call out 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 designs be used to generate possibilities and identify 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 and interpreted by AIs influence care opportunities and decisions?

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

How are both personalization and scalability redefined and designed in an era of big data, missing data, and sparse data?

How should we design autonomous and semi-autonomous systems that provide therapeutic value and will be anticipated, accepted, and embraced by human actors in diverse environments?

How should AIs be designed, adapted, and regulated as trusted members of care teams?

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

We believe that mindful consideration of these questions teams is particularly important in healthcare contexts where complex issues concerning emotions, power, inclusion, decision making, and responsibility are key human variables. Working with the powerful material of AI in such environments presents the potential for tremendous advancement as practiced within a reflective and careful design framework.

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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