Applications of Digital Health and Patient Monitoring in Opioid Addiction Recovery

Modernizing Regulatory Practices for Artificial Intelligence Driven Medical Tools

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction

In the past year, 93,000 people have died from drug related overdoses (*CDC Provisional Drug Overdose Data*, 2021). For the 3 million Americans currently suffering from Opioid Use Disorder (OUD), unfortunately options for recovery are largely ineffective (Azadfard et al., 2021); 91% of patients relapse at least once, and 80% of patients relapse within a month of a detoxification program (Smyth et al., 2010). This low retention in treatment is caused by a lack of continuity in care. Patients at do not receive the necessary clinical oversight and access to resources at home, where most of recovery takes place. The majority of patients in addiction recovery are from lower income backgrounds or homeless. As their home environments are not conducive to recovery, it is crucial that they maintain a connection to their support system in the clinic at all times (Manhapra et al., 2018).

Fortunately, advancements in digital health are enabling physicians to stay connected with patients outside of clinic and helping them predict patient outcomes to deliver better preventative care. The PositiveLinks team has demonstrated exciting progress in the use of mobile health to improve retention in care for patients managing HIV. These patients tend to have significant demographic overlap with patients with OUD (Dillingham et al., 2018). Recent studies have corroborated the use of digital therapy to treat mental health illnesses such as depression and anxiety, which are often underlying co-morbidities to addiction (Glasner-Edwards et al., 2016). Building on these technologies, I will propose the development of a digital therapy service for patients suffering from opioid addiction. This service will consist of a medication tracker which logs when patients consume their withdrawal medications as well as their cravings/withdrawal symptoms. Using this data to predict a patient's risk of relapse, a digital therapy chatbot will inform the patient of coping strategies, connect them to critical resources/support systems, and alert their physician.

While predictive analytics of patient outcomes may seem to be a positive advancement towards more equitable healthcare, algorithmic bias in both the data and the model can lead to the exact opposite, disadvantaging certain marginalized groups. An understanding of how the model was developed and how the data was sourced is crucial to qualifying the results of its predictions (Panch et al., 2019). Considering both the technical aspects of development and the social factors influencing the engineers of the model creates a holistic understanding of the context surrounding healthcare algorithms, making its users more aware of why their tools make certain decisions. Contrarily, continuing to blindly trust the model will likely further propagate and automate existing systemic biases. In healthcare this can have severe consequences, preventing patients who need live-saving care from receiving appropriate medical resources. Such was the case with the failure of the Optum Risk Score Algorithm (OSRA), which embodied significant racial bias preventing Black patients from receiving critical healthcare resources (Obermeyer et al., 2019). I refer to Black patients as those with African ancestry receiving healthcare in the US without necessarily a US citizenship.

Due to the sociotechnical nature of digital health and its potential for algorithmic bias, I will provide a comprehensive proposal for research in both the technical and social aspects of the subject. In the technical section, I will propose an application of digital health in combatting OUD with a medication tracker and digital therapy chatbot. To address the social challenges posed with digital health, I will analyze the failures in the model utilized by Optum to identify patients with complex illnesses and advanced healthcare by investigating the network builders that contributed to the development of the Optum Algorithm Network (OAN) and the process by which this network formed, referred to as translation. An enriched understanding of both the social and technical forces that influence innovation in predictive healthcare, a subset of digital health, will help inform the design process to account for unforeseen impacts on underrepresented minority groups, especially in treating opioid addiction. An otherwise strict focus on the technical design would neglect the broader impact that engineers have on societies.

Technical Topic

Over 3 million Americans have been diagnosed with Opioid Use Disorder (OUD) (Azadfard et al., 2021). Of the 93,000 drug overdoses in 2020, over 70% can be attributed to opioid abuse largely due to the recent rise in highly addictive synthetic opioids (e.g. heroine, fentanyl, carfentanil) (*Drug Overdose Deaths | CDC Injury Center*, 2021). Unfortunately, recovery from OUD is incredibly difficult; the process takes several years, and 91% of patients relapse at least once. Traditional detox programs are largely ineffective, as 59% of patients relapse within the first week and 80% relapse within the first month of sobriety (Smyth et al., 2010). The most effective form of recovery programs called Medication Assisted Treatment (MAT) tend to be a combination of detoxification, withdrawal medication prescription (e.g. Suboxone), and weekly psychological counseling. However, 55% of patients are not retained in treatment after one year. Current approaches are ineffective due to a lack of continuous oversight. Addiction is a chronic illness that affects patients 24/7, and their living circumstances tend to be discouraging towards recovery; the majority of patients tend to be homeless or from low income backgrounds (Manhapra et al., 2018). When patients are disengaged from treatment outside of the clinic, and return to environments that promote addiction, they are more likely to relapse. Fatal drug overdoses have risen 30% since the start of the pandemic due to virtualized, low-touch healthcare, and they will continue to rise unless this lack of continuity in care is addressed. Further, in the first month that a patient disenrolls from treatment due to relapse, they are over 4 times more likely to fatally overdose due to increased cravings and lowered tolerance (Davoli et al., 2007). Finding a means to address this attrition will save tens of thousands of lives every year by keeping patients in treatment and preventing deadly overdoses.

To improve outpatient treatment retention, I propose the development of a medication tracker for Suboxone sublingual strips and a Digital Therapeutic Chatbot (DTC). The medication tracker will inform providers of patients' medication consumption habits, and therefore their withdrawal patterns. This data will also inform the DTC, which will support patients with coping strategies and alert their peer support group at stressful times in their recovery. The patient's counselors/peer support can then reach out to the patient and take appropriate steps to mitigate the risk of relapse between clinic visits. The medication tracker will be a WiFi and Cellular enabled IoT device programmed in C++. To maintain the security compliance required by the Health Information Portability and Accountability Act (HIPAA), the device will utilize the HTTPS protocol to encrypt all patient health information in transit. The data will be maintained in a NoSQL MongoDB database, which will be encrypted at rest with clustered replicas to ensure data security and integrity. The DTC and interfacing web application for providers will be developed in JavaScript frameworks (i.e. ReactJS and NodeJS) and deployed on Linux webservers hosted by Amazon Web Services cloud infrastructure. The DTC will communicate with the patient via SMS using the Twilio API and will modify its interaction with the patient based on an assigned risk score for relapse. This risk score will be calculated based on the patient's recovery history, including positive urine drug screens, previous relapse frequency, etc., as well as medication consumption information from the tracker. I believe this approach of providing tools for remote care will improve patient retention due to previous success with similar technologies for patients managing other chronic illnesses such as HIV, depression, and anxiety. The patient groups in these studies had similar demographic backgrounds as those suffering from OUD, which suggests potential efficacy for this digital health solution to address opioid addiction as well (Campbell et al., 2021).

STS Topic

As important decisions begin to rely heavily on artificial intelligence-based insights, it is important to recognize the algorithmic biases that can negatively influence its outcomes (Mullainathan & Obermeyer, 2017). The OSRA predicted which patients would yield high costs in healthcare for insurers. Assigning risk based on predicted future healthcare costs is a common standard in health insurance forecast models (Bates et al., 2014). This model runs predictions on an estimated 200 million patients per year. The 97th percentile of these patients would then be enrolled in a preventative care management program, where they would receive additional medical attention to deter escalating their condition and the cost of treatment. This algorithm suffers from a significant amount of racial bias, as it is more likely to select a White patient for this treatment program than a Black patient with the same degree of illness. A Black patient assigned the same risk score as a White patient tends to have 26.3% more chronic illnesses than their racial counterpart. Accounting for this bias would increase the enrollment of Black patients in the program from 17.7% to 46.5% (Obermeyer et al., 2019).

This disparity tends to be attributed to the design of the algorithm label, or the value the model predicts. The current claim is that predicting the cost a patient yields to the insurer is an inaccurate representation of eligibility for the advanced care program, as Black patients tend to use less hospital resources than White patients, controlled by illness (Fiscella et al., 2000). Designating the label choice as the source of the bias disregards the various implicit social influences that also contributed to the model design. Assigning priority to only the technical contributors obscures the influence that systemic causes of racial bias imparted on the development of the model. Investigating these factors can reveal important social dynamics such as the underlying causes for low medical resource utilization by Black patients, diversity on the model design team, and precedent set by healthcare corporations to obscure proprietary models. By acknowledging the influence of such issues in algorithmic bias, in addition to its technical faults, the medical professionals utilizing these algorithms can gain insights into why their tools make racially biased decisions and take counteractive steps to ensure equitable access to healthcare for all patients.

Drawing on Actor-Network Theory, I will show how high barriers to healthcare access for Black patients and cost-predictive standards set in proprietary corporate machine learning models contributed to the algorithmic bias in OSRA. To demonstrate this relationship, I will draw on Actor-Network Theory (ANT). This framework analyzes how network builders develop heterogenous actor-networks of human and non-human actors to achieve a common goal. The process of building this network is called translation (Cressman, 2009). In this case study, the network builders of the OAN are the engineers who contributed to the development of OSRA. Specifically, I will investigate issues with the translation of the OAN that enabled algorithmic bias during its stabilization, resulting in a model that became an adversarial actor for Black patients and the failure of the network. To support my claim, I will analyze the research that initially exposed the faults of OSRA, as well as various press reports and public statements from Optum at the time. Further, I will investigate reports on other machine learning models contemporary to OSRA to draw parallels and uncover networks that may have influenced its development.

Conclusion

The technical project will materialize the concept described above, a medication tracker and digital therapeutic chatbot designed to extend care from the clinic to the patient's home. Further, the deliverable will outline data from preliminary feasibility studies, examining its viability in a clinical setting and patient/provider attitudes towards adopting the product. In the STS project, I will use ANT to provide an improved understanding regarding how network builders failed in developing the OAN during translation, which ultimately caused the network to function as an adversarial actor against African American patients in the overarching network of US healthcare. Together, these projects will address the broader sociotechnical issue of equitable predictive analytics in healthcare by providing a technical implementation for a specific use case in opioid addiction and a valuable framework to analyze and prevent algorithmic bias.

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