Developing a Decision Support System to Detect and Enhance the Response to Clinical Deterioration in Patients Receiving Outpatient Care for Cancer

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Introduction: A common cause of preventable harm is the failure to promptly detect and properly respond to clinical deterioration. Although inpatients are more likely experience deterioration, occurrence in outpatients is more challenging because detection processes rely primarily on the patients and their families and the response arm is much less robust. Ambulatory patients recovering from an acute event (e.g., surgery, illness), or those undergoing potentially hazardous treatments (e.g., chemotherapy) are at the highest risk for clinical deterioration. The primary objective is to create, refine, deploy and evaluate software tools and an artificial intelligence (AI) predictive model to support a reliable surveillance-and-response system to prevent harm from unexpected all-cause clinical deterioration in outpatients receiving cancer treatment.

Figure. The elements of the planned surveillance component include real-time passive data capture, at-will active patient reporting of non-routine events (NREs), weekly patient self-reported outcome variables (PROMs). These data feed into the AI model which will drive the response arm. Patient deterioration in outpatient cancer care in this study is operationalized as Unplanned Treatment Events (UTEs) extracted from the EHR.

Methods: We are starting the second year of a 4- to 5-year project. The patient data from our first study (planned enrollment of 60 patients, each studied for 6-8 weeks) will be used to create the AI model. A second study’s data (2020-1) will be used to validate the AI model while a third study (2021-2) will evaluate the fully integrated system (including the response arm).

Active Surveillance: We developed and pilot tested user-friendly mobile apps to collect patient-reported NREs and PROMs as well as a REDCap database for patient demographic and other study variables. We also developed processes to assure that patients enter the required weekly data.

Passive Surveillance: We developed processes to capture, via a Fitbit Charge wrist activity monitor, real-time patient data including heart rate, steps, and sleep parameters. We are using the Google Maps app to capture geolocation data. All of these data are downloaded on a weekly basis.

Response Arm: We have begun to consider how best to deliver the results of the predictive AI model to responsible clinicians. This involves not only determining what to say (e.g., “Mr. Jones has a 83% probability of an unplanned treatment event in the coming week. Do you want to text him?”) but who to send this to and the technical capabilities and logistics to do so.

Patient Engagement: A critical determinant of success will be to engage patients and family members enrolled the study. We have developed several methods to elicit patient input.

Results: As of November 1, 2019, we have enrolled in the first study nine head-and-neck cancer patients receiving outpatient chemo- or radiation therapy. We have successfully captured FitBit data
from all patients and 16 patient/family reported NREs have been reported from 6 patients (range 1-5/patient). There have been two UTEs in two different patients. Enrollment is ongoing.

**Conclusions:** In this complex study, we have created innovative methods and tools to capture rich data from cancer outpatients that can be used as inputs to predictive AI models. We will present some of the challenges we have overcome as well as our preliminary results.