Abstract

Alcohol use disorder (AUD) and other substance use disorders (SUDs) are chronic conditions with high relapse rates and limited access to continuing care. Automated patient monitoring and support systems (APMSSs) offer a promising solution by using smartphones to monitor symptoms, predict relapse risks, and deliver personalized interventions. Curtin and colleagues have demonstrated the feasibility of smartphone-based ecological momentary assessments (EMAs) and machine learning models to predict daily relapse risk. However, effective implementation requires optimizing how patients receive and engage with these automated messages. This study evaluates various supportive language dimensions: validation of distress, expression of caring, and acknowledgment of feelings, and their impact on patients' perceptions of usefulness and support in daily messages from an APMSS. Forty participants in early recovery from AUD will complete a 21-day study, receiving personalized messages generated by a locally run large language model based on their EMAs and relapse risk predictions. Participants will rate these messages on perceived support and utility. Findings will inform best practices for delivering AI-driven supportive messaging and optimizing automated continuing care for individuals in recovery from SUDs.

Alcohol and other substance use disorders (SUDs) are serious chronic conditions, characterized by high relapse rates[1,2], substantial co-morbidity with other physical and mental health problems[2,3], and an increased risk of mortality[4,5]. Too few individuals receive medications or clinician-delivered interventions to help them initially achieve abstinence and/or reduce harms associated with their use[3], and even fewer receive continuing care. Continuing care, including both risk monitoring and ongoing support, is the gold standard for managing chronic health conditions such as diabetes, asthma, and HIV. Yet continuing care for SUDs is largely lacking despite ample evidence that SUDs are chronic, relapsing conditions[3,6,7].

Clinical researchers are now in the early stages of developing automated patient monitoring and support systems (APMSSs) to address this unmet need for SUD continuing care[8,9]. These APMSSs can deliver scalable and cost-efficient personalized care by using smartphones to both monitor patients' symptoms and relapse risks and deploy algorithms that recommend interventions and other supports that precisely target those symptoms and risks each day. Curtin and colleagues have confirmed that smartphone-based ecological momentary assessments (EMAs; i.e., brief surveys completed each day on patients' phones) are feasible and effective for long-term (up to a year) monitoring of patients with SUD[10,11]. Furthermore, they have developed an algorithm that can accurately predict future lapses back to substance use with high temporal specificity (i.e., lapses within the next day) using these EMAs as inputs[9]. These same algorithms can also identify the most important risk factors for a lapse during that next day, which can be used to recommend daily interventions or other supports specific to that patient.

The APMSSs developed by Curtin and colleagues and others[9,11,12,13] have enormous potential to fill the gap in continuing care for SUD. These systems can provide continuous risk monitoring and deliver daily personalized messaging to patients to guide them in addressing threats to their recovery. The algorithms created by Curtin et al. can predict lapse risk probability, key contributing risk factors, and recommended interventions daily for each patient. However, to successfully implement these APMSSs for clinical benefits, we must first determine how best to provide these algorithm outputs to patients such that patients find the information to be supportive, useful, and personally relevant.

There is substantial evidence that the language used in supportive and other advice messaging is crucial for patients to trust and follow advice when it is provided by healthcare professionals (e.g., doctors) in healthcare and similar settings. Classic research by Burleson and others has suggested that effective supportive advice messaging should 1) validate felt distress, 2) express caring, and 3) acknowledge participants' feelings[14,15]. Advice messages that **validate felt distress** convey that the patient's feelings are legitimate and do not criticize or punish these feelings, but rather acknowledge them as a step towards fixing the problem[14,16]. Messages that **express caring** convey positive intentions, willingness to cooperate with the patient's goals, acceptance of the patient, and availability to help[16,17,18]. Messages that **acknowledge feelings** convey interest in listening to the patient, encourage them to express and explore their emotions, hypothesize about their feelings ("I bet that was difficult" "I imagine you felt …"), and restate or reflect feelings[14,16,19,20,21]. Advice messaging that includes language consistent with each of these dimensions has been demonstrated to increase patient receptiveness and engagement with the advice provided to them[15].

This rich literature on supportive advice messaging provides us with a strong foundation on which to craft daily messaging to patients from an APMSS. However, it is not clear which of these three dimensions of messages will generalize to a context where messages are received from an automated system rather than a human advisor (e.g., a doctor). Patients may view any message delivered by an APMSS as less supportive and useful than when it is delivered by a human healthcare professional, particularly when messages rely on language characteristics that seem inherently human (e.g., empathy, caring). Conversely, the Computers as Social Actors paradigm[22] suggests when algorithm-based technologies present humanlike attributes, users will perceive these technologies as social actors and transfer human-human communication scripts to human-technology interaction[23,24]. Given this uncertainty, the proposed research will directly manipulate and evaluate the impact of each of the above three dimensions (validation of distress, expression of caring, acknowledgment of feelings) on patients' perceptions of the usefulness and support offered by daily messages from an APMSS.

Method

Participants: We will recruit 40 participants in early recovery (1-8 weeks of abstinence) from moderate to severe alcohol use disorder for a 21-day longitudinal study. Participants will be recruited through print and targeted digital advertisements and partnerships with treatment centers. We will require that participants 1) are 18 years or older, 2) can write and read in English, 3) have at least moderately severe alcohol use disorder (>= 4 self-reported DSM-5 symptoms), 4) are abstinent from alcohol for 1-8 weeks, and 5) are willing to use a single smartphone (personal or study provided) while on study.

Procedure: Participants will complete one EMA each afternoon on their smartphone (see Measures below). These EMAs will serve as inputs into the lapse prediction model developed by our laboratory[9]. This lapse prediction model will generate personalized feedback each day on the participants' lapse probability, the most important contributing risk factors, and a recommended intervention, activity, or support to address their risk. These messages will be delivered to participants each morning starting on the sixth day of their participation (to allow for sufficient input for accurate predictions). This information from the prediction algorithm will be embedded within a longer message that includes language characteristics that 1) validate felt distress, 2) express caring, and 3) acknowledge participants' feelings. These messages are generated through the use of a locally run (for privacy reasons) large language model (Meta Llama 3) that has information both from the lapse prediction model and from the participants' EMAs. For safety reasons, message content generated by the LLM is reviewed each morning by research staff to confirm its appropriateness before providing it to participants. These messages are generated by the LLM with prompts to include language characteristics that vary across the three dimensions such that each participant will receive 2 messages in each of the 8 combinations of these three dimensions (i.e., 16 messages total across 16 days). Upon receipt of each message, participants will rate how useful the message was to their recovery and how supportive they perceived the message to be on a brief measure that has been used in previous research on automatic text messaging support systems.

Measures: Each EMA will include 10 items and take approximately 30 seconds to complete. Across items, participants report dates/times of any previously unreported past alcohol use. rated the maximum intensity of recent (i.e., since the last EMA) experiences of craving, risky situations, stressful events, and pleasant events, and their current affect on two bipolar scales: valence (Unpleasant/Unhappy to Pleasant/Happy) and arousal (Calm/Sleepy to Aroused/Alert). They also rate the likelihood of encountering risky situations and stressful events in the next week and the likelihood that they would drink alcohol in the next week (i.e., abstinence self-efficacy). These EMAs are delivered to participants' smartphones each afternoon at a time determined convenient to them.

On receipt of each daily support message, participants will evaluate their utility and supportiveness on a 7-item survey that includes specific Likert-scaled items measuring if the message was helpful, supportive, easy to understand, interesting, written personally for them, relevant to their situation, and likable). This measure yields a single total score but can also support item-level analyses.

Analyses: We will analyze the total score and individual items from the message rating scale in separate multi-level mixed effects linear models with factors for the three language dimensions: validate felt distress (included or not), 2) express caring (included or not), and 3) acknowledge participants feelings (included or not). We will evaluate the main effects and interactions among these three dimensions.

Timeline and Future Directions

Data collection will occur over spring and summer, and analyses and manuscript writing will occur in the fall. The conclusions of this study will be used to determine how language in messages delivered by APMSSs should be used in future studies conducted at the Addiction Research Center.

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