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Toward a just-in-time adaptive intervention to reduce emerging adult alcohol use: Testing approaches for identifying when to intervene

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Abstract

To identify critical periods for just-in-time adaptive interventions (JITAIs), we measured time-varying correlates of drinking (e.g., stress, mood) daily to predict near-term alcohol use. Emerging adults (aged 17-24; n=51) who reported past-month alcohol use used SARA, an app use designed to assess substance use, for 30 days. Participants completed daily process measures of stress, mood, hopefulness, free time, fun, and loneliness. Candidate variables for prediction of next-day drinking included a contextual factor (day of the week), between-person factors (age, sex), and within-person factors (daily process measure responses) as well as daily process measure noncompletion. We compared two approaches to predict next-day use. From the daily process measure responses, Approach 1 used the current day's survey responses; whereas, Approach 2 used the deviation of daily responses from the participant's average response in prior days. Backward model selection identified candidate variables to include in the logistic model. Each model's discriminatory power was determined using the area under the curve (AUC). Toward identifying critical periods for interventions, decision rules for when next day alcohol use was likely are reported for the better performing approach. Approach 1 included day of the week, hopefulness, stress, and participant sex (AUC=0.76). Approach 2 included day of the week, and deviation in hopefulness rating (AUC=0.71). Decisional cutpoints are provided for the better performing model. Approach 1 provided better prediction than Approach 2. Decisional tools for identification of near-term alcohol use in emerging adults opens the door for JITAIs to reduce drinking and prevent consequences of use.

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1. Introduction

Alcohol use is a major cause of preventable morbidity and mortality in the U.S (Rehm et al., 2009; Roerecke & Rehm, 2013). Emerging adulthood, including later adolescents into the early 20s is a developmental period (typically beginning around ages 17-19) wherein youth begin to navigate transitions to adult roles (e.g., higher education, entering the workforce). This period represents a window of opportunity for interventions that target risky drinking at a critical developmental juncture. Alcohol use typically initiates and peaks during this developmental phase (Marshall, 2014), with 9.4% of 12-17-year-olds and 54.3% of 18-25 year-olds reporting past-month alcohol use in 2019 (Substance Abuse and Mental Health Services Administration (SAMHSA), 2020). Emerging adults have the highest rates of smartphone ownership of any age group, with 96% owning smartphones ("Mobile Fact Sheet," 2021). Given the ubiquity of smartphone usage, mobile health (mHealth) assessments and interventions are particularly well-suited for emerging adults.

1.1 mHealth for alcohol use assessment and intervention

Facilitated by the proliferation of cell phones, smartphones, and wearables, the use of ecological momentary assessments and daily process measures are increasingly common in substance use research (Cohn et al., 2011; Collins et al., 2003; Fridberg et al., 2019; Heron et al., 2017; Serre et al., 2015; Shiffman, 2009; Stone et al., 2007; Wray et al., 2014). Ecological momentary assessments and daily process measures both fall under the broader umbrella of intensive longitudinal data collection designs, with ecological momentary assessments often referring to data collection that occurs multiple times per day and daily process measures typically referring to data collection occurring once daily (Shiffman, 2009). For the purposes of the current report, all intensive longitudinal data collection will be referred to as daily process measures.

Much of the prior work using daily process measures to assess substance use has been conducted among college students, establishing both within- and between-person associations with substance use behavior (e.g., Serre et al., 2015; Shiffman, 2009; Wray et al., 2014). While within-person states might vary day-to-day or even moment-to-moment, between-person traits are relatively stable. For example, in an early study of same-day predictors of college student drinking, heightened within-person affective experiences were associated with more drinking regardless if it were positive or negative although alcohol-related problems were only associated with negative affect (Simons et al., 2005). Subsequent investigations have replicated and extended early work, largely focusing on constructs such as craving, mood, stress, motives for use, and social contexts (for systematic reviews and meta-analyses see Heron et al., 2017; Hutton et al., 2020; Serre et al., 2015; Votaw & Witkiewitz, 2021; Wen et al., 2017). Recently, constructs such as loneliness and hopefulness have become increasingly of interest to understand changes in drinking behavior, with calls for more research on these topics (Horigian et al., 2020; Hwang et al., 2020; Ingram et al., 2020; Jeste et al., 2020; Lee, 2020). Prior work has indicated that less loneliness and more hopefulness are protective against alcohol and other substance use behaviors, at least at the between-person level (Brooks et al., 2016; Savolainen et al., 2020). However, the impact of within-person variations in these experiences are unknown. The integration of established within-person risk factors for use, such as stress and mood, with emerging constructs implicated in alcohol use, such as loneliness, may inform future, more robust mHealth interventions for emerging adults.

1.2 Just-in-time adaptive interventions (JITAIs)

Prior reviews of mHealth interventions have highlighted the acceptability, convenience, scalability, and potential for mHealth to reduce substance use (Kazemi et al., 2017). Unfortunately, to date mHealth interventions in youth have had small effect sizes for behavior change in general and alcohol use specifically (Fedele et al., 2017; Hutton et al., 2020; Mason et al., 2015). JITAIs are a novel intervention delivery framework that aim to harness advances in mobile and wireless technology to promote behavior change. JITAIs deliver interventions in the moment when they are most needed, in the person’s natural environment (Klasnja et al., 2015; Nahum-Shani et al., 2015, 2018). JITAIs use contextual, person-specific, and time-varying information (e.g., time of day, location, mood, craving) to determine how and when to intervene (or not to intervene) in order to optimally impact a proximal outcome, such as drinking, while also minimizing unnecessary treatment and burden. Despite increasing use and appeal of JITAIs, there is a critical need for research on the development and effectiveness of these interventions (Nahum-Shani et al., 2018). In order to develop empirically-based JITAIs, identification of windows in which intervention delivery would be beneficial to a person is necessary.

To date, few studies have extended beyond establishing associations between factors such as craving, mood, and stress with drinking to develop decision tools, such as rules or algorithms to classify when an event is expected, to identify moments of high risk for near-term drinking when JITAIs may be beneficial. Decision tools to detect or predict proximal alcohol use, taking into consideration both within- and between-person constructs, is critical to the development of highly effective JITAIs targeting alcohol use. This can focus on either detecting when alcohol use has started, to deploy interventions during the drinking episode aiming to reduce the amount of use or prevent consequences from use (e.g., driving after drinking), or it can focus on predicting when near-term drinking is likely so that an intervention can be deployed before drinking begins to either prevent or reduce the amount of subsequent drinking. An example of the former used mobile phone sensing to determine when emerging adults were actively drinking (Bae et al., 2018). This study showed promise for the use of smartphone sensing (e.g., phone movement, phone screen unlocks, call durations, letter deletions) to detect when alcohol use is actively occurring. An example of the latter is a recent study that assessed homeless adults multiple times a day about risk factors for alcohol use to predict imminent alcohol use, defined as drinking within the next four hours, and deployed interventions based on the current risk of imminent drinking (Businelle et al., 2020; Walters et al., 2021). Taken together, prior work highlights two complementary lines of research for the development of JITAIs to reduce alcohol use and alcohol-related harms, that is detection of drinking initiation to prompt interventions once alcohol use has commenced and prediction of when alcohol use is forthcoming to prompt interventions to prevent or reduce alcohol use and associated consequences before it occurs.

1.3 Current study

Here, we focus on upstream constructs that may precipitate drinking by predicting next day alcohol use based on daily process measures from the prior evening. In this way, we aim to identify the day prior to an expected drinking episode to inform the deployment of JITAIs. Identification of periods where individuals are vulnerable to engage in health risk behaviors (i.e., alcohol use in the current study) is a critical step toward improving health by intervening on an 'as needed' basis (Inbal Nahum-Shani et al., 2015). However, how best to use transient daily information to predict next day alcohol use so as to inform intervention delivery is still largely unknown. As such, the immediate goal of the current study is to evaluate the predictive ability of two candidate approaches using daily process measures, in combination with contextual and between-person factors, for classification of near-term alcohol use, defined as next-day drinking. The first candidate approach uses daily process measure responses to predict next day drinking. The second candidate approach uses the deviation in daily process measure responses from the individuals typical (i.e. average) responding to date, to predict next day alcohol use (Approach 2). These two candidate approaches were compared to identify which approach provides better prediction of near-term alcohol use for subsequent use in a JITAI. The ultimate goals of this work is to: (1) inform the approach used to create classifier decision tool to identify intervention windows in the development of future mHealth JITAIs, and (2) to use the resultant decisional tools from the current project to inform the development of a JITAI to prevent drinking or reduce consumption on a subsequent day in emerging adults.

2. Methods

SARA is a smartphone application designed to foster an engaging environment to assess substance use in emerging adults. The initial study, described previously (Rabbi et al., 2017, 2018), enrolled a community-based sample of participants from the emergency department who (1) were medically stable, (2) understood English, (3) had access to a mobile phone, (4) screened positive for past-month heavy drinking (≥4 drinks for females and ≥5 drinks for males) or recreational cannabis use and (5) were able to provide informed consent or assent (with parental consent if younger than 18 years old) between August 2017 and February 2018 (N=74). The study was approved by the Institutional Review Board of the University of Michigan (HUM00121553) and registered at ClinicalTrials.gov (NCT03255317). Participants downloaded the SARA app onto their personal phone. The study was a micro-randomized trial (MRT), which is a study design wherein participants are repeatedly randomized over the course of the study to evaluate the effect of intervention components and whether intervention component effects vary by time and/or context toward the goal of optimizing mHealth interventions. The primary study outcomes of this MRT, which involved re-randomizing participants multiple times daily over 30 days to various engagement strategies (e.g., reciprocity, non-monetary reinforcement) with the goal of identifying engagement strategies that promote daily survey completion, have been reported elsewhere (see Nahum-Shani et al., In press for detailed methods and enrollment flow diagram; see https://www.methodology.psu.edu/ra/adap-inter/mrt-projects/ for a resource on microrandomized trials). The present analytical sample (N=51) included a subset of the original sample with past-month alcohol use, inclusion criteria are described below (see Procedures).

2.1. Participants

Of those participants included in the analytic sample (N=51), 52.94% were female (n = 27), with an average age of 20.47 years old (range 17-24 years old). The majority of participants identified as White (n=35, 68.63%), with 11.76% identifying as Black or African American (n=6), and most identifying as non-Hispanic (n=45, 88.24%). Most of the sample (72.55%) reported completing some college or higher education. At baseline, 84.31% (n=43) of participants reported heavy drinking in the past month (>4 drinks for females or >5 drinks for males) and approximately half (n=25) of the participants reported cannabis use in the past month.

On average, participants responded to daily process measures on 20.76 (SD=7.56) of the 30 days, leaving approximately one-third of the daily process measures uncompleted. Participants reported alcohol use approximately one day per week (M=4.2 days, SD=4.2) with drinking occurring most frequently on Friday and Saturday. See Figure 1 for percent of drinking days by day of the week. The results of each approach for predicting next day alcohol use are provided separately and then compared below.

2.2. Procedures

Study procedures have been documented in detail previously, including detailed descriptions of the SARA interface and development (Rabbi et al., 2017, 2018). In brief, the SARA app was built around an aquarium environment where participants received points toward additional fish for completion of assessment measures, in addition to other theoretically-grounded strategies to encourage engagement in assessments. The SARA app was developed with the primary focus of being engaging for emerging adults to provide a scalable assessment tool with minimal use of monetary rewards in preference of developmentally and culturally appropriate rewards for engagement (e.g., points, fish, gifs). Of relevance to the current analyses, participants completed a baseline Timeline Followback to document prior 30-day alcohol use (Sobell et al., 1996; Sobell & Sobell, 1995, 1996). In the app environment, participants were prompted to complete daily process measures between 6PM and 12AM about factors related to alcohol use, such as daily stress level, mood characteristics, and feelings of hopefulness and loneliness, adapted from multi-item surveys (e.g., Hoyle et al., 2002; Lippman et al., 2014). All items used in the current examination, their associated response scales, and descriptives are found in Table 1. Participants were asked to complete daily process measures in the evening to capture states throughout the current day (see Nahum-Shani et al., in press. For detailed description of study design and rationale). In addition, participants were asked weekly via app prompts, on Sunday evening, to report past-week alcohol use using a 7-day Timeline Followback (Sobell and Sobell 1996). Participants earned $1 for every three consecutive daily process measures completed and $0.50 for completion of the survey on Sunday.

Inclusion criteria for the analytic sample were those participants who reported past-month drinking and who completed at least one daily process measure and at least one weekly assessment of the 7-day Timeline Followback during the course of the 30 day study (N=51).

2.3. Analyses Plan - Evaluating candidate approaches to predict future alcohol use.

To inform the deployment of JITAIs to reduce alcohol use in emerging adults, we compare two approaches for predicting when an individual is vulnerable to drinking. The daily process measure features considered in each approach differed. Approach 1 used the current day's survey responses to predict next day drinking. Approach 1 was selected to evaluate if proximal states, without consideration or prior responding, could provide adequate prediction of next day alcohol use. Approach 2 used the deviation in the current day's responses for each of the daily process measures from the individual's typical response up until the current day (i.e., time-varying person-mean centered) to predict next day drinking. Approach 2 was selected to consider the possibility that the extent to which an individual's responses vary from their prior usual responses may have implications for alcohol use prediction. Other variables considered for inclusion in both of the approaches included: the day of the week, participant age, sex assigned at birth, and noncompletion of daily process measures. Noncompletion of daily process measures (also termed noncompliance, missingness, or lack of engagement), is common and well-documented in mHealth studies, with similar rates of noncompletion found in meta-analytic results (Wen et al., 2017). In the current sample, 30.8% of the daily process measures were not completed, and therefore noncompletion of daily process measures was included as a candidate indicator variable for next-day alcohol use to assess for the possibility that it was systematically related to subsequent alcohol use. All other candidate variables (i.e., day of the week, age, sex) had no missing values.

We compared the predictive accuracy of Approach 1 and Approach 2 to ascertain if cumulative information from previous days would outperform the current day's responses alone. All analyses were conducted in SAS 9.4 (SAS Institute, Cary, NC). For both Approach 1 and Approach 2 the analysis plan followed two steps as described below, followed by a comparison of the predictive accuracy of the two approaches.

2.3.1. Step 1: Selecting what factors to use to predict next day drinking.—Separately for each approach, the feature of interest from the daily process measures (Approach 1: current day's responses, Approach 2: deviation of the current day's response from the individual's prior average response), along with day of the week, noncompletion of daily process measures, age, and sex were entered into a backward model selection method, which accounted for repeated measurement within participants (Su & Lin, 2007). A fixed value selection criterion of p equal to or less than 0.10 was employed, with the variable with the highest p-value removed iteratively until all p-values satisfied this stopping rule (Chowdhury & Turin, 2020).

2.3.2. Step 2: Evaluating and cross-validating prediction models.—*Separately for each approach, t*he selected candidate factors from Step 1 were included in generalized estimating equations with independent covariance structures, which account for the nested nature of the data, to predict next-day drinking. Although other data analytic procedures are possible (e.g., decision trees and other machine learning approaches), we tested these two approaches using generalized estimating equations logistic regression as a pragmatic starting point. Using logistic regression for prediction has the benefit of being a familiar and established approach for prediction among behavioral scientists (Steidtmann et al., 2013), making this procedure easier to communicate and interpret even when used for prediction as opposed to hypothesis testing.

Predictive performance of each of the models (i.e., Approach 1 and Approach 2 models) was evaluated using the area under the receiver operator characteristic (ROC) curve (AUC). The AUC provides a metric of a model's discriminatory ability between dichotomous outcomes, in this case drink or not drink on the following day. AUC is commonly used in psychometric analyses and is robust against uneven base rates and non-normal distributions (McGraw & Wong, 1992). AUCs range from 0 to 1 with 0.56, 0.64, and 0.71 denoting small, medium, and large AUC effect sizes, respectively (Pencina et al., 2012; Rice & Harris, 2005). For a model with no discriminatory power, the AUC will be 0.5. To evaluate out-of-sample model fit, we conducted a 10-fold cross-validation procedure where the participants were partitioned into 10 unique groups. For each iteration, one group (approximately 10% of participants) was held out as the testing dataset. The remaining nine groups (approximately 90% of the participants) were collapsed as the training dataset. For each iteration, the prediction model was fit to the training dataset and evaluated on the testing dataset. The difference in the AUC between the training and testing dataset was averaged across the iterations to obtain a measure of out-of-sample prediction.

2.3.3. Prediction approach selection and decision tools for when to deploy a just-in-time adaptive intervention.—

Toward identifying critical times to deploy a JITAI using a prediction rule, we selected the approach with the higher AUC. To inform decision tools for when to deploy an intervention, we selected the nearest top left point on the ROC curve corresponding to maximal sensitivity and specificity. We report the cutoff of the predicted probability from the nearest top left point on the ROC curve, that is the value that maximizes the discriminatory ability between drinking and non-drinking days. Finally, we generated decision tools for when alcohol use was predicted based on the estimated model parameters for each possible combination of values for the predictors. These decision tools are presented below to inform future JITAIs.

3. Results

3.1. Approach 1: Predicting next day alcohol use using today's survey responses

3.1.1. Step 1: Using the backward model selection, daily rating of hopefulness and stress along with the day of the week and sex were included in the best fitting model. Hopefulness and stress were positively associated with next-day alcohol use, as was male sex. Compared to Saturday, days leading into the weekend (Wednesday, Thursday, Friday) had higher odds of next-day alcohol use, whereas days at the start of the week (Sunday, Monday, Tuesday) were associated with lower odds of next day drinking. See Table 2 for the model summary.

3.1.2. Step 2: An ROC curve was constructed to show model prediction of next day alcohol use (see Figure 2), with an AUC of 0.76. Employing a 10-fold cross-validation procedure, the average difference in AUC between the training and testing datasets was 0.02 (average lower confidence limit= −0.01, average upper confidence limit=0.05).

3.2. Approach 2: Predicting next day's alcohol use using the deviation from the individual's average response to date.

3.2.1. Step 1: The best-fitting Approach 2 model selected using backward selection included the deviation in an individual's hopefulness rating from their average hopefulness rating to date and the day of the week (see Table 3 for a summary of the selected model).

3.2.2. Step 2: The selected model (see Table 3) was used to predict next-day alcohol use. When participants reported feeling more hopeful than typical, that is, as the deviation in hopefulness became increasingly positive, next-day drinking was more likely. Day of the week followed a similar pattern to that described in Approach 1, with higher odds of next-day alcohol use toward the end of the week and lower odds early in the week. Model performance is depicted in the ROC curve shown in Figure 3, with an AUC of 0.71. The 10-fold cross-validation procedure resulted in an average difference in AUC between the training and testing datasets was 0.02 (average lower confidence limit= −0.02, average upper confidence limit=0.07).

3.3. Comparison of prediction approaches.

Both approaches resulted in AUCs with large effect sizes (Pencina et al., 2012; Rice & Harris, 2005). Approach 1 (current day's survey responses) outperformed Approach 2 (deviation from prior responding) with AUCs of 0.76 vs. 0.71, respectively. The difference in AUCs of 0.05 is minimal and unlikely to lead to clinically significant differences in identifying when to deploy JITAIs to intervene on alcohol use. Nonetheless, the simplicity of using daily responses, without the need to consider deviation from prior responses, led us to retain Approach 1 as the preferred prediction approach.

The nearest top left point on the ROC curve generated using Approach 1, which corresponds to predicted probability 0.20, was selected to produce maximal sensitivity and specificity when discriminating between next days with and without drinking. Based on this selected cutpoint, participant days in which the predicted probability is above 0.20 are classified as days in which next-day drinking is likely. This cutpoint yields 0.70 specificity and 0.68 sensitivity, providing similar accuracy in identifying drinking days (68%) as non-drinking days (70% of the non-drinking days were correctly classified). Based on Approach 1, we used the independent variables in the model rather than the predicted probability, to create decision tools. These decision tools for when next day drinking is expected for every combination of day of the week, sex, stress and hopefulness ratings are presented in Figure 4. In general, people are at risk of drinking the next day when stress is relatively high, and even modest values of hopefulness will push people over the threshold to drink. This relationship becomes more pronounced on days of the week that are high-risk for next-day drinking, like Thursday and Friday.

4. Discussion

Prior work has identified several within-person states and between-person traits that are associated with alcohol use (for systematic reviews and meta-analyses see Heron et al., 2017; Hutton et al., 2020; Serre et al., 2015; Votaw & Witkiewitz, 2021); however, the need persists to leverage correlates of alcohol use into classifiers that can prospectively identify when next day alcohol use is likely. Decisional tools are a critical step toward developing mHealth JITAIs to prevent alcohol misuse and subsequent consequences, particularly geared toward emerging adults who are typically technology-oriented and are in need of interventions to curtail risk trajectories that could lead to negative outcomes in adulthood. However, what approaches provide the most accurate prediction of next day alcohol use is largely unknown. We compared two approaches for predicting when alcohol use is likely, the first used current day's daily process measure responses and the second approach used the deviation in current responses from time-varying typical responses. Next-day alcohol use was predicted with in-sample AUCs of 0.77 when using daily responses and 0.71 when using the deviation of typical responses, and with out-of-sample prediction exceeding 0.70 for Approach 1. These findings suggest that within-person time-varying correlates of alcohol use (e.g., stress, hopefulness), when used in combination with between-person traits (sex) and context (day of the week) can identify days in which the risk for next day drinking is high. Knowing on what days emerging adults are at risk for next day drinking may inform the design of interventions that trigger psychosocial or motivational content on days classified as high risk to prevent next day drinking. This can inform future JITAIs by indicating when (i.e., on what days) emerging adults are at risk for next day drinking so that intervention delivery may be considered. Future work to identify which intervention would be best to deliver and whether emerging adults are receptive to this intervention on days of high risk is needed.

Within-person reports of hopefulness and stress were included in the better-performing model (i.e., Approach 1). Hopefulness is a novel construct as it relates to time-varying alcohol use and warrants further investigation in future research given greater hopefulness predicts next day drinking in this sample. Hopefulness may capture anticipatory excitement about planned next day drinking episodes, suggesting that JITAIs targeting reductions in drinking intensity or drinking-related risky behavior (e.g., drinking and driving) may be indicated. Prior research on the association between stress and alcohol use has focused on same-day associations with varying findings showing that increased stress can lead to either increases or decreases in alcohol use (Dvorak & Simons, 2014; Simons et al., 2010; Swendsen et al., 2000). In this study, we found evidence of increased stress predicting next-day alcohol use. These findings may justify a wider temporal window of evaluation when assessing the relationship between time-varying constructs, such as hopefulness and stress, and downstream (e.g., next day) alcohol use.

The prediction of next day alcohol use, and detection of a decisional cutpoint, sets the stage to deploy JITAIs to reduce risky drinking and consequences of use in emerging adults. Similar methods to those used here have been used to identify responders and non-responders to depression treatments (Steidtmann et al., 2013) and to identify suicide crises among high-risk adolescents (Czyz et al., 2020); however, this is the first study, to the best of our knowledge, using this technique to identify critical windows for mHealth interventions for alcohol-focused JITAIs. The identification of decisional cutpoints for when next day alcohol use is expected is an important step in the development of a JITAI based on time-varying factors (Nahum-Shani et al., 2015, 2018). The decisional cutpoints for when a JITAI is needed to prevent next-day drinking indicate that surveying stress and hopefulness only provides added predictive value on some days of the week. Regardless of stress and hopefulness ratings, for males, next day drinking is expected on Thursday and Friday, coinciding with the most frequent drinking days (Friday and Saturday). Next-day drinking was not likely on Sundays, or Mondays and Tuesdays for females, regardless of stress and hopefulness ratings. These high and low drinking probability days reduce the number of days where self-report items need to be queried to identify high-risk drinking days, minimizing participant burden. On the remaining days of the week, the prediction of next-day drinking is sensitive to stress and hopefulness ratings, showing that on days where drinking is moderately likely, higher stress and hopefulness, especially when experienced in combination, are important indicators of next day drinking.

Instead of assessing drinking daily, our study focused on identification of daily markers of alcohol use (alcohol use was queried weekly using a 7-day Timeline Followback) for several reasons. First, social desirability bias could lead youth to underreport daily, to avoid receiving messages that they may perceive as trying to dissuade them from drinking or having fun, though some work points to the opposite effect with under-reporting of quantity of use, though still comparable reporting of frequency of use, when using Timeline Followback measures that retrospectively report on longer spans of time (i.e., 6 weeks, Dulin et al. 2017). Second, for some people daily inquiry could have a priming effect, leading to short-term increases in drinking due to this reminder (Buu et al., 2020), which could be particularly true for samples who are not interested in reducing their drinking (e.g., precontemplators). Third, identification of drinking without asking about it per se has the potential benefit of reducing assessment reactivity, a benefit for those trying to understand daily factors associated with drinking, however, when focusing on intervention development, some researchers may prefer to harness assessment reactivity via self-monitoring of alcohol use (often with feedback graphs) as a way to facilitate behavior change (Clifford et al., 2007; Kaminer et al., 2008; Kazdin, 1974; Maisto et al., 2007; Schrimsher & Filtz, 2011; Walters et al., 2009). Regardless, with prediction tools such as the one developed here, alcohol use can be probabilistically predicted, reducing the need for frequent direct assessment of drinking by researchers, and identifying daily contextual targets for mHealth interventions.

Prior JITAIs for alcohol use have focused on addiction treatment samples to provide relapse prevention tools. For example, adult-focused relapse prevention studies have deployed JITAIs based on when an individual goes to a self-identified high-risk location, identified based on GPS (Gustafson et al., 2014). Youth-focused relapse prevention has involved daily text messages followed by tailored intervention messages (Gonzales et al., 2014, 2016). In the current study, which focused on a not-in-treatment sample of emerging adults that engage in risky drinking, we used within-person, self-reported factors in addition to sex and day of the week to predict near-term alcohol use. It may be that the combination of passive data collection, such as GPS, along with self-reported states and between-person traits, may optimize prediction and increase the accuracy of predicted alcohol use to inform future JITAIs.

The current findings should be considered within the context of the study's limitations and future directions. First, the prediction of near-term alcohol use is only as good as the assessments that are considered. Prediction of near-term alcohol use may be improved if different or additional dynamic within-person daily measures, stable between-person participant traits, or contextual information are assessed. Multimodal data, including both self-report and passive data collection is likely to provide richer information to inform prediction. By layering self-report daily process measures with contextual factors (e.g., day of the week) and passive collection from mobile phones, wearables, and social media, prediction accuracy may be further increased. Second, participant days with incomplete data were removed from the generalized estimating equation procedure. Though daily process measure noncompletion was included as a candidate indicator of next-day drinking in these analyses, and was not retained in either model selection routine. Future work should further investigate whether and what pattern of noncompletion may improve prediction of use and the impact of contemporary techniques for missing data handling on prediction accuracy. In particular, development and validation of data imputation methods for MRTs are needed. Third, a future study replicating the selected approach and cutpoint decision tool in a new and larger sample of emerging adults will be necessary to determine the utility of this decision tool for delivering effective JITAIs, and may be extended to predict quantity of alcohol use, especially since different expected quantities of alcohol use may be addressed through different JITAIs. An additional consideration for future work is to compare different analytic approaches. This study used logistic regression and ROC curves to predict alcohol use and evaluate performance. This method has been used previously for behavior prediction and cutpoint identification in the social sciences (Czyz et al., 2020; Steidtmann et al., 2013). Fourth, in consideration of the potential for assessment reactivity, unintentionally priming alcohol use, or social desirability bias, the current study assessed alcohol use weekly via the reliable and valid Timeline Followback (Sobell et al., 1979, 1996) instead of directly asking about alcohol use every day. This design decision was weighed against the possibility of introducing recall bias, and a one week recall period was selected based on prior work indicating this may be an ideal recall pattern for capturing variability in alcohol use and other risk behaviors (Buu et al. 2014). Future work to determine the optimal frequency of alcohol (or other substance use/risk behavior) assessment to balance these competing concerns is warranted. In summary, future directions for this work include collection of larger samples, additional candidate predictors, and consideration of other prediction methods including the burgeoning field of machine learning and contributions from computer science that may (or may not) improve on the current methods.

Toward the development of JITAIs that can prevent or reduce risky drinking and related problems, this preliminary study provides initial evidence that daily process measures in combination with participant characteristics (sex) and context (day of the week), and without daily assessment of alcohol use, can provide decisional cutpoints for when near-term drinking is expected among not-in-treatment emerging adults that engage in risky drinking. These findings serve several purposes. First, they can inform alcohol study designs to allow researchers to measure alcohol outcomes without the direct assessment of alcohol, thus minimizing risk of assessment reactivity and participant burden. Second, using daily process measure responses, in addition to sex and day of the week, to predict near-term (next day) alcohol use, resulted in accurate prediction of 76% of drinking days. Third, decisional cutpoints and rules were constructed to identify critical periods for interventions to address upstream motives for risky drinking and, with future replication and refinement with larger samples, could be applied for use in JITAIs targeting prevention or reduction in drinking among emerging adults.

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Abbreviations:

JITAI	Just-in-time adaptive intervention
ROC	receiver operating characteristic
AUC	area under the curve

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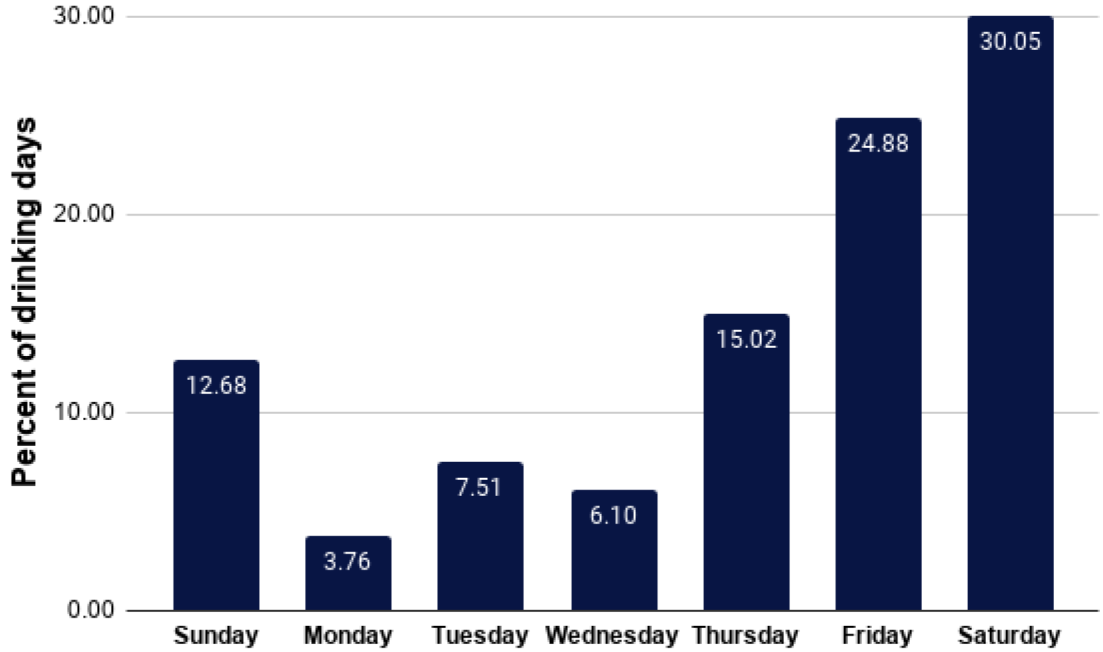

Figure 1.

Alcohol use by day of the week over the course of the 30-day study.

Drinks are based on weekly 7-day Timeline Followback self-reported alcohol use.

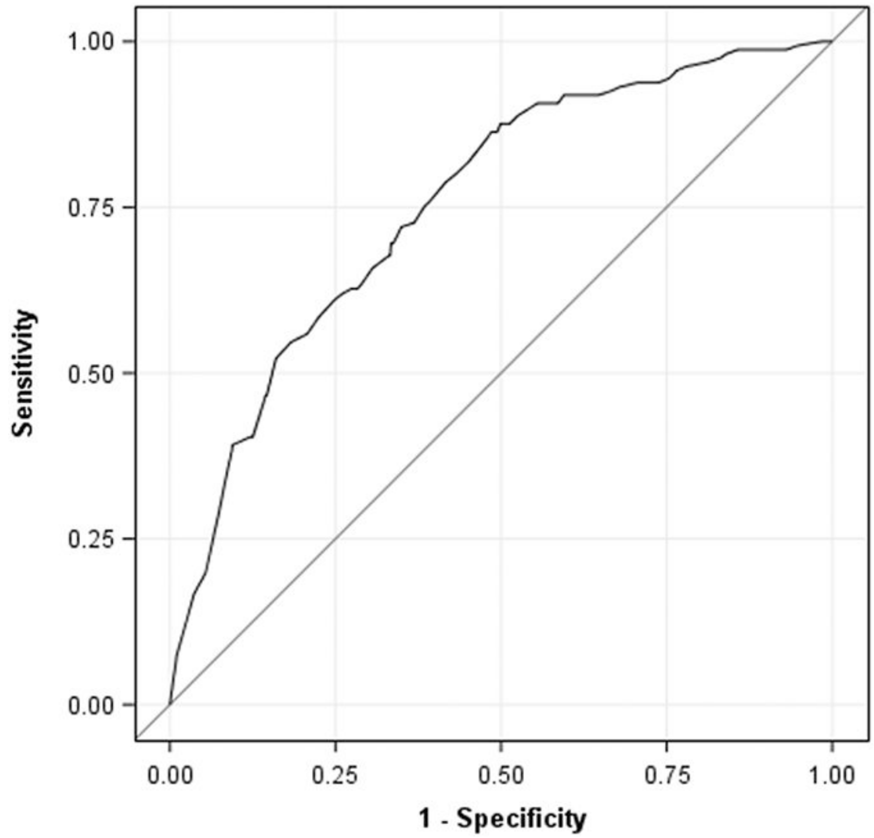

Figure 2.
ROC curve using Approach 1 model to predict next day alcohol use, AUC=0.76.

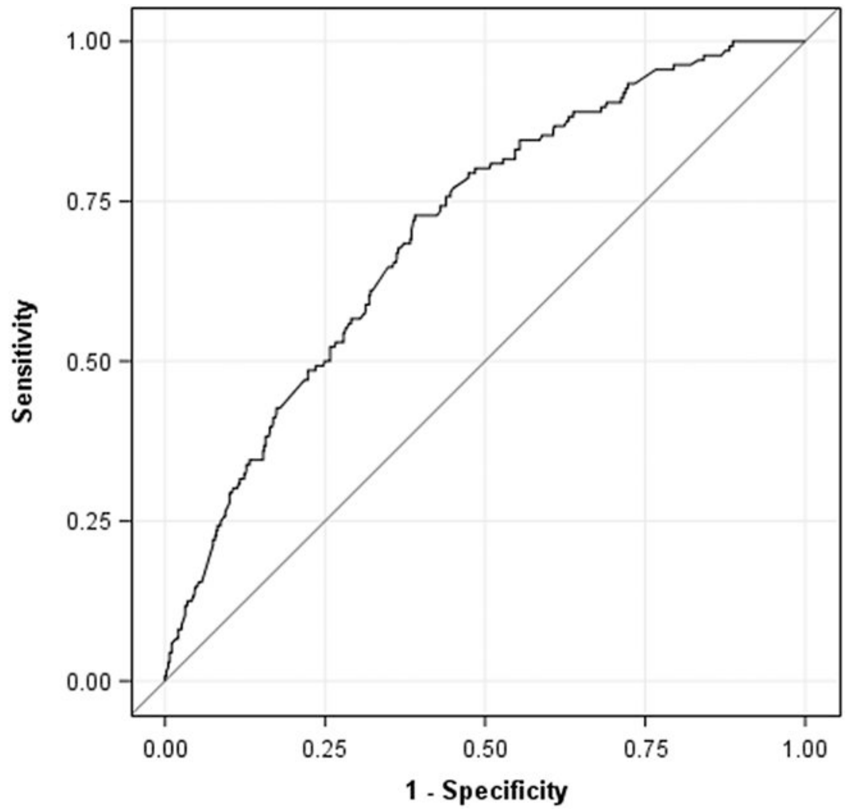

Figure 3.
ROC curve using Approach 2 model to predict next day alcohol use, AUC=0.71.

Females are likely to drink the next day

On Wednesday, if (stress>2 and hopefulness>2) or (stress=2 and hopefulness=4)

On Thursday, if (stress=4) or (hopefulness>2) or (stress>1 and hopefulness>0) or (stress=1 and hopefulness=2)

On Friday, if (stress>1) or (hopefulness>1) or (stress=1 and hopefulness=1)

On Saturday, if stress>2 and hopefulness=4

Males are likely to drink the next day

On Monday, if stress=4 and hopefulness=4

On Tuesdays, if (stress=4 and hopefulness>2) or (stress=3 and hopefulness=4)

On Wednesday, if (stress=4) or (hopefulness>2) or (stress>0 and hopefulness>1) or (stress>1 and hopefulness>0)

On Thursday and Friday, regardless of stress and hopefulness ratings

On Saturday, if (stress>2 and hopefulness>1) or (stress=2 and hopefulness=3) or (hopefulness=4)

Figure 4.

Approach 1 decision tool for when to identify next day drinking (overall model cutpoint=0.20).

Note: Both males and females are unlikely to drink the next day on Sundays; females are also unlikely to drink the next day on Mondays, Tuesdays, or Saturdays. Stress and hopefulness scores range from 0 (not at all) to 4 (a lot/very).

Table 1.

Daily process measures

Topic	Question	Range	Mean (*SD*)
Stress	How stressed are you today?	0 (not at all) to 4 (a lot)	1.9 (0.7)
Mood - arousal	How are you feeling today?	0 (sleepy) to 10 (alert)	5.2 (1.5)
Mood - valence	How are you feeling today?	0 (negative) to 10 (positive)	5.4 (1.2)
Hopefulness	Do you expect good things will happen to you tomorrow?	0 (not at all) to 4 (very much)	2.3 (0.7)
Free time	How much free time have you had today?	0 - 24 hours	8.6 (5.3)
Fun	How much fun have you had today?	0 (not at all) to 4 (a lot)	1.7 (0.6)
Loneliness	How lonely or left out have you felt today?	0 (not at all) to 4 (very)	1.1 (0.7)
Novelty	How new and exciting has your day been?	0 (not at all) to 4 (very)	1.7 (0.6)

Table 2.

Approach 1 logistic model predicting next-day alcohol use.

Predictors	Odds Ratio	95% Confidence Interval	p-value
Intercept	0.06	0.03-0.13	<0.01
Sex (ref=female)	2.01	1.01-4.02	0.05
Day of week (ref=Saturday)			
Sunday	0.23	0.07-0.74	0.01
Monday	0.55	0.26-1.14	0.11
Tuesday	0.70	0.31-1.57	0.39
Wednesday	1.56	0.75-3.20	0.23
Thursday	3.14	1.44-6.83	<0.01
Friday	3.89	2.12-7.14	<0.01
Stress	1.17	0.98-1.38	0.08
Hopefulness	1.29	1.05-1.57	0.01

Table 3.

Approach 2 logistic model predicting next-day alcohol use.

Predictors	Odds Ratio	95% Confidence Interval	p-value
Intercept	0.15	0.09-0.27	<0.01
Day of week (ref=Saturday)			
Sunday	0.32	0.11-0.97	0.04
Monday	0.60	0.28-1.30	0.19
Tuesday	1.24	0.53-2.87	0.62
Wednesday	1.79	0.84-3.84	0.13
Thursday	3.66	1.70-7.89	<0.01
Friday	2.71	1.47-5.01	<0.01
Deviation in hopefulness	1.27	1.01-1.58	0.04