

Predicting the initial lapse using a mobile health application after alcohol detoxification

By

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Executive Summary

This dissertation reports on a predictive modeling study of the initial alcohol lapse after patients left residential care. The data were collected via a mobile health application, Addiction-Comprehensive Health Enhancement Support System (A-CHESS). A-CHESS was designed to offer ongoing support to alcohol addiction patients who have returned to their own community after completing inpatient treatment programs. Patients may access A-CHESS services at any time anywhere to help them cope with their recovery.

A lapse is defined as an initial setback while the relapse means the return to previous problematic drinking behavior (Witkiewitz & Marlatt, 2004). The prediction and prevention of the initial lapse—which is defined, in this dissertation, as the first lapse after a period of abstinence—is important because the initial lapse often leads to subsequent lapses (within the same lapse episode) or even relapse (Chih et al., 2014; Witkiewitz & Marlatt, 2004). The prediction of the initial lapse may allow preemptive intervention via A-CHESS to be possible. In addition to the first chapter as the introduction of the problems and context, this dissertation consists of the other three sections (or papers); each section presents the efforts to address different challenges faced in the development of such a predictive model in A-CHESS. The first challenge is the validation of the instrument used in the A-CHESS Weekly Check-in; the second challenge is the study of A-CHESS use behavior before the initial lapse; and the third challenge is to develop a comprehensive predictive model of the initial lapse.

Major findings from this dissertation are briefly summarized below:

1. In chapter 2, among the ten items used in the Weekly Check-in, two factors were found. One factor is called the recovery risk factor including these five items—sleeping problems, depression, urge, risky situation, and relationship troubles. The other factor is called the recovery protection factor including these five items—abstinence confidence, the attendance of AA meetings, spiritual activities, other activities, and the time spent with families/friends. These two factors are highly reliable and clearly distinct from each other. An overall recovery progress score was calculated as the difference between these two factor scores (i.e., the recovery protection score minus the recovery risk score). Both the overall recovery progress and the recovery protection scores were found to be predictive of the initial lapse.
2. In a latent profile analysis presented in chapter 3, a list of multi-level, across-service use measures was examined. Three underlying A-CHESS use profiles (i.e., low, medium, and high users) were found. The relationships between latent profiles and the initial lapse were explored. Compared to Medium A-CHESS users, high users used more in coping competence related A-CHESS services and actively participated in the online social support activities. However, the differences of the initial lapses between A-CHESS use profiles were not statistically significant. Implications of the findings in the light of the comprehensive system use measurement model and the literature were discussed.
3. In chapter 4, a review of relevant literature regarding predictors of alcohol use behavior was provided. The logistic regression-based predictive model that contains all predictors (called the Full Model) was developed. Through variable selection procedures, a model that contains only two significant predictors (i.e. gender and recovery progress) was also

developed (called the Simplified Model). This simplified model showed good predictability in 10-fold cross-validation with the area under receiver operating characteristic curve (AUC) up to 0.69, as compared to 0.55 in the Full Model. However, the Full Model showed better predictability using data from later lapse episodes, with AUC up to 0.75, as compared to 0.65 in the Simplified Model. Therefore, the Simplified Model may be better applied to new cases, while the Full Model for later lapse episodes. The findings provide an opportunity to improve the accuracy of an existing weekly lapse prediction service provided in A-CHESS (Chih et al., 2014).

Several challenges exist to applying mobile technology in healthcare (Kumar et al., 2013). The steps taken in this dissertation to address these challenges have been proven fruitful. The major findings are practical, and the predictive model has the potential to be implemented in A-CHESS. However, this dissertation is an important step toward the development of innovative addiction care services that are continuous, patient-centered, personalized, and cost-effective. Further work is needed in order to apply and refine the current findings into the existing care processes.

1 Introduction

1.1 Background and Needs

1.1.1 Needs for Innovation in Alcohol Relapse Prevention

In 2010, an estimated 22.1 million people (8.7 percent of the U.S. population aged 12 or older) in the U.S. were classified with alcohol dependence or abuse (Substance Abuse and Mental Health Services Administration, 2011). A central characteristic of alcoholism and other addictive behaviors is their chronically relapsing nature (Larimer, Palmer, & Marlatt, 1999). Relapse reduces the quality of life for the drinking individuals and their families, puts great strains on family relationships and huge burden on society through crime, accident, healthcare costs, and reduced productivity (Ettner, 2006). Although a variety of alcohol addiction treatments were developed and implemented, as many as 80% of the program participants would relapse completely once they finished and left the programs (Bradizza, Stasiewicz, & Paas, 2006; Miller, Walters, & Bennett, 2001).

People striving to change problematic drinking behavior often experience an initial setback, a transitory state or so-called lapse(s), which likely leads to a full return to their previous, problematic drinking behavior called relapse (Witkiewitz & Marlatt, 2004). The course from initial lapse(s) to relapse was described using the metaphor as “falling off the wagon”— it implies falling off abstinence (Marlatt, 1996). In a study of the transitions between three underlying drinking statuses, i.e. non-drinking, moderate drinking and heavy drinking of those just finishing treatment programs, researchers found that up to 23% of non-drinkers and 38% of

moderate drinkers at the time of leaving the treatment program would become heavy drinkers within 6 months (Witkiewitz, 2008). For that reason, extending addiction care beyond traditional, one-time inpatient treatment episodes is very critical for these patients who desire to keep a sober life while returning back to their own communities.

To prevent “falling off the wagon”, the development of extended monitoring and treatment interventions after regular inpatient programs has been ongoing. With the extended monitoring approaches, addiction counselors may monitor the treatment progress and offer early and personalized intervention to prevent people from the lapse-relapse cycle (McLellan, McKay, Forman, Cacciola, & Kemp, 2005). Few such programs utilize outpatient group-based interventions or remote case management via regular telephone calls. The studies have shown moderate benefits (Coviello, Zanis, Wesnoski, & Alterman, 2006; Krampe et al., 2006; McKay, 2005). In a recent review of these continuous care interventions, researchers concluded that despite the encouraging outcomes, many patients did not engage in such programs (McKay, 2009). They have called for the development of innovative interventions that are “both accessible and attractive to a wide variety of individuals with addiction problems, utilize a number of service delivery systems and methods, promote sustained participation in ongoing disease management, are responsive to changes in symptoms and functioning over time, are economically feasible, and are able to incorporate medications as well as other therapeutic supports (McKay, 2009, p.15)” The emerging mobile information and communication technologies may be able to bring this idea into realization.

1.1.2 A-CHESS—an Emerging Mobile Health Solution

Smartphone devices and applications have been fast growing in the recent years. About one in every two American adults owns a smartphone in the year of 2012 (Fox & Duggan, 2012). With smartphones, people may interact with instant and customized information. People may also connect with each other via video conferencing, e-mails, text messages and social networking applications. Future mobile computing, just like electricity and water, has the potential to become a 24/7 commodity in our life (Hurlburt, Voas, W. Miller, & Miller, 2010).

Health care is taking the advantage of the mobile technology. Currently, more than 8000 mobile health (mHealth) applications are available to be used on major mobile platforms (mHealth news, 2011). MHealth can be defined as the use of mobile information and communication tools to improve health and health services. The wireless connectivity offered by existing mobile devices, like smartphones, enables mHealth applications to offer 24/7 continuous support to patients facing different health challenges. These mHealth applications address various issues in health care from physical fitness and chronic disease management to medical diagnosis. The emerging mobile technologies have shown a great potential to mitigate health disparity and improve population health (Akter & Ray, 2010; Arora, Peters, Agy, & Menchine, 2012; Rajput et al., 2012).

The emerging mHealth technology has the potential to offer innovative solutions in alcohol relapse prevention (Gustafson et al., 2005). In the year of 2005, with the grant support from the Robert Wood Johnson foundation, a panel consisting of experts both inside and outside the addiction field along patients and families, met together at the University of Wisconsin Madison

to envision new addiction treatments that would take advantages of the readily available technology in the near future (Gustafson et al., 2005). They were asked to basically abandon the existing human-based addiction treatment tradition and consider what and how future technologies could be used to meet the needs of addiction patients and their families.

Based on the ideas from this panel meeting, scientists and engineers at the Center for Health Enhancement Systems Studies (the CHESS Center) at the University of Wisconsin Madison have developed a mobile relapse-prevention app suite called Addiction-Comprehensive Health Enhancement Support System (A-CHESS) that can run on smartphones. Researchers at the CHESS Center have over 20 years of experiences in designing interactive communication technologies to support people facing chronic and life threatening illnesses (Gustafson et al., 2002, 2008). A-CHESS is built upon an influential relapse prevention model and a sound psycho-social motivation theory, plus the latest mobile technology (Gustafson, Boyle, et al., 2011). A randomized controlled trial to test the efficacy of A-CHESS has just ended in 2012.

1.1.3 Continuous Monitoring of Risks and Early Detection of Lapses

Operated on the latest mobile communication technology, A-CHESS shows a great potential in addiction relapse prevention (Johnson, Isham, Shah, & Gustafson, 2011). With the ubiquitous computing power on a mobile platform, A-CHESS puts the constant monitoring and support tools into the hands of addiction patients. A-CHESS currently offers more than 20 different informational, interactive and social networking services, such as online Discussion Groups, Easing Distress, Personal Stories, Panic Button, GPS Tracking, Health News, Library Articles,

and Weekly Check-in...etc., to support alcohol dependent individuals who have just left the residential care.

A-CHESS may facilitate the communication of patients' needs to their peers and doctors. On one hand, patients with A-CHESS may communicate their needs to their counselors and peers at any time. On the other hand, A-CHESS offers the counselors the ability to continuously monitor their patients' status through the data collected in A-CHESS. Patients with A-CHESS were prompted to complete a weekly Check-in that contains questions asking patients' perceived risks of drinking as well as their drinking status in the past week (i.e. the last seven days). From the Check-in data and other readily available data, like A-CHESS usage data, clinicians may be able to continuously monitor patients' situations, which can potentially lead to customized assistance to individual patients. Aided with the dual communication channels and the rich information and support provided within A-CHESS, patients are in a better position to resist the temptation and keep staying sober.

With such a great promise, nevertheless, A-CHESS has not achieved its true potential in preventing patient from lapsing. Alcohol lapse can happen at a sudden but however may have a trend to follow (Collins et al., 1998; Witkiewitz & Masyn, 2008). As mentioned in previous paragraphs, A-CHESS collects remotely and continuously patient status reports including the Weekly Check-in and A-CHESS use data. The Weekly Check-in and use data have been used by both patients and their counselors as monitoring tools. However, no formal and systematic evaluation of either Weekly Check-in questions or A-CHESS use data has been done. There is also no mechanism in place to assess the risks of lapse and to offer decision support as to when

to intervene. The aim of using A-CHESS to monitor and assess the risks of lapse in a timely manner has not been fully realized.

A risk assessment (or prediction) of alcohol lapses is the key to prevent patients from falling off the wagon and coming back to their previous drinking behaviors (i.e. relapse). As alcohol relapse prevention programs are moving toward a continuous mode of post-treatment intervention at the communities where patients reside, it becomes more important to understand the determinants of alcohol lapses and the methods available for assessing them outside the clinical settings on a continuous basis (McLellan et al., 2005; Rounsaville, 2011). The enormous data available instantly from patients via mobile technologies can potentially lead to new understandings (Dobkin & Dorsch, 2011; Rajput et al., 2012), in this case, knowing who may be at risk of drinking and when to intervene (Johnson et al., 2011).

Although A-CHESS offers tools for patients and care providers to monitor patients' symptoms continuously, no prediction mechanism has been studied to offer decision support as to when and may be how to intervene. The aim of this dissertation was to utilize the available data collected in A-CHESS to offer risk assessment and prediction of the initial lapse on a weekly basis. Using data from a current trial, a probabilistic model that support clinicians (and the patients) in making decision regarding patients' risks of their initial weekly lapse was developed.

1.2 Issues in the Development of A-CHESS Lapse Risk Assessment

1.2.1 The Development of A-CHESS Weekly Check-in

The strength of A-CHESS is its ability to collect data instantly and remotely. A-CHESS currently prompts patients to fill out Weekly Check-in questions asking patients to assess their personal as well as situational factors of lapses. The set of questions used in A-CHESS Check-in were adapted from Brief Alcoholism Monitor (BAM), a survey instrument developed by researchers at the University of Pennsylvania and the Treatment Research Institute with the support from the U.S. Department of Veterans Affairs, Center of Excellence for Substance Abuse Treatment and Education and the VISN 4 MIRECC (Cacciola et al., 2013; Cacciola, Alterman, Oslin, & McKay, 2008). BAM was intended to be used on a monthly basis at outpatient settings as a part of the concurrent recovery monitoring (McLellan et al., 2005). It is designed to be self-administered based on patients' perceived levels of the risk factors occurring in the past 30 days at the time of assessment.

BAM is a relatively new survey instrument for alcohol addiction relapse monitoring. It is a short and easily-filled out survey (Cacciola et al., 2008). Cacciola and his colleagues (2012) found a different factor structure than the one outlined in their own survey instrument in Cacciola (2008). This discrepancy is likely due to different items used in their exploratory factor analysis. Therefore, the proposed risk and protective factor structure in BAM has not been validated. Moreover, BAM was adapted from a monthly (30 days) assessment in its original form to a weekly (7 days) assessment tool in A-CHESS. To increase the readability and usability of the questions on a smartphone screen (4-5 inch screen) the items have been shortened and the scale

were redesigned with a color coding system. In this dissertation, the analyses to examine the factor structure as well as validity and reliability of these modified BAM questions used in A-CHESS Weekly Check-in have been done in order to use the A-CHESS Weekly Check-in as a tool for assessing weekly lapse risks.

1.2.2 The Impact of A-CHESS Use on Lapses

Compared to those who receive usual care A-CHESS patients can receive additional information and support provided in A-CHESS anytime anywhere. When A-CHESS patients feel the needs to seek out information and support, they can simply turn on A-CHESS services while those in the usual care would have a hard time to locate any help at the moment.

A-CHESS offers patients different services (e.g., Panic Button, Easing Distress and My Team) to nurture their autonomy, competence and relatedness—the three most fundamental, psychological needs outlined in Self-Determination Theory (SDT)—at each step of their recovery process (Gustafson, Shaw, et al., 2011; Ryan & Deci, 2000). Patients may benefit differently from their different A-CHESS use patterns. In eHealth studies, the use patterns of different web-based applications have been found to be associated with various health outcomes (Han et al., 2009; Shaw et al., 2007; Wise, Yun, & Shaw, 2000). It is likely that the smartphone-based A-CHESS use patterns would be potentially related to patients' tendency to lapse or not. Therefore the impact of A-CHESS use patterns on lapse(s) was explored in this dissertation.

From the weekly lapse assessment perspective, we were interested in knowing whether and especially what A-CHESS use patterns would be the most predictive of lapses in the following week. Are there different underlying use patterns? Is the overall use or the use near the lapse

events more important to offer the indication of potential future lapses? Are accumulated use patterns more important than recent use patterns in predicting weekly lapses? Would different use patterns lead to different results meaning that whether some A-CHESS use patterns are more helpful than the others? These issues will be explored in this dissertation.

1.2.3 The Needs for a Practical Risk Assessment Tool of Initial Weekly Lapse

Initial and subsequent lapses are different in nature. The initial lapses have been found to be related to the increased chances of subsequent lapses, the further reduction of self-efficacy and the negative reinforcement on the negative affect (Baker, Piper, McCarthy, Majeskie, & Fiore, 2004; Witkiewitz & Marlatt, 2004). Existing literature about risk assessment of initial and subsequent lapses are scarce due to the general emphasis on the long term relapse outcomes (McKay & Weiss, 2001). Although several factors such as self-efficacy, negative mood and coping skills were identified to be associated with lapses (Högström Brandt, Thorburn, Hiltunen, & Borg, 1999; Rounsaville, 2011; Shiffman et al., 2007; Witkiewitz & Masyn, 2008), the resulting factors and the distinctions between initial and subsequent lapses were neither constant nor clear. Most importantly no further effort was there to offer clinicians a practical tool that include a standard data collection method as well as a guideline for decision making in potential lapse situations. The focus of this dissertation will be the development of a practical risk assessment model for initial lapses. The developed model will be validated using the selected second lapse dataset and a receiver operating characteristic (ROC) curve analysis.

1.3 Significances

The development of effective post-treatment intervention to prevent the “falling off the wagon”—a process from initial lapses to relapse—has become more and more important. A-CHESS, by utilizing the advanced information and mobile communication technologies, may play a significant role in shaping future alcohol addiction treatment. One of the key functions of A-CHESS is to facilitate the continuous communication/monitoring of patient status and offer decision support to addiction counselors (and patients). The counselors need to know when to intervene and patients need to know how to seek out support especially after they are out of treatment facilities and back to their own communities. This dissertation reported on the work to achieve the following goals in order to realize this potential of A-CHESS. First, the psychometric properties of an existing A-CHESS Weekly Check-in questionnaire and its potential as an instrument for lapse risk assessment were evaluated (see chapter 2). Second, whether A-CHESS use behaviors were related to the weekly lapses and what the relationships were if they existed were further explored and discovered (see chapter 3). Last, based on the Weekly Check-in data as well as A-CHESS use behavior patterns, weekly lapse risk assessment models for initial lapses were developed (see chapter 4). This model offered a set of decision rules for treatment providers in determining when to intervene.

To achieve these goals, the following research questions were addressed:

RQ1. Whether factors of the modified BAM in A-CHESS Weekly Check-in were predictive of the initial lapse in the following week?

RQ2. What A-CHESS use patterns were predictive of the initial lapse in the following week?

RQ3. How likely would a patient report an initial lapse in the following week based on his or her demographics, distal risk factors, overall recovery progress score from the Weekly Check-in, and A-CHESS use patterns?

This dissertation may lead to the following practical and theoretical contributions in the fields of alcohol addiction treatment and systems engineering:

For alcohol addiction treatment:

1. The validated BAM survey used in A-CHESS Weekly Check-in may offer a useful instrument and tool for counselors to assess and patients to self-assess their risks of lapse weekly.
2. The prediction model of the initial lapses may support addiction counselors in making decisions about when and potentially how to intervene such events.
3. This work may contribute to scarce lapse prediction literature.

For systems engineering:

1. The development of A-CHESS use measurement system may serve as an example of systematic evaluation of system use behavior in mHealth interventions.
2. The resulting system use patterns may offer insights in the understanding of mHealth system use in general and among our user population in specific.
3. The exploration of the A-CHESS use measurement system may provide the evidence about the relationships between A-CHESS use behaviors and the outcomes (i.e. alcohol lapses) of system use.

4. Based on this dissertation, the resulting initial lapse prediction model can be used to expand the existing functionality of A-CHESS.

1.4 Limitations

It is important to note here that some limitations did exist in this dissertation. Since the focus of this study is to develop initial lapse risk assessment model, the data used for model development collected from A-CHESS will be limited to the scope and the properties of the collected data. Based on data availability, a lapse is defined in this dissertation as any reported drink event in a prior week. There are various definitions of alcohol lapses (such as the amount and/or duration of drinks) (Donovan, 1996; Maisto, Pollock, Cornelius, Lynch, & Martin, 2003; McKay, Franklin, Patapis, & Lynch, 2006). Even a formal guideline about clinical classification of alcohol dependence or abuse is available (American Psychiatric Association, 2000). However, using these definitions often required more detailed data about alcohol consumption which are not currently available in the existing ACHES trial. However the definition of alcohol lapse used in the A-CHESS Check-in and in this study is simple and may better avoid potential recall biases than collecting more detailed drinking data from the patients.

Another drawback of not matching to the definitions of alcohol lapse to other studies or clinical standards may lead to potential doubt about the generalizability and clinical relevance of this work. However, the risk assessment model based on the proposed definition of alcohol lapse may lead to better treatment outcomes because it provides more sensitive decision support about any drink potentials as opposed to only over a certain amount or duration of drinks when the timing

of offering intervention can be too late. Since the project aim is limited to the initial lapse, relapse was not addressed in this dissertation. Nevertheless the lapse risk assessment models developed in this dissertation may help to improve long term relapse outcome because it may prevent the progression from lapse to relapse.

1.5 Document Organization

The following document is organized into these sections. In Chapter 2, a paper examining the psychometric properties of the Weekly Check-in was presented. In Chapter 3, a paper exploring the underlying A-CHESS use patterns and their relationships to the subsequent initial lapses was presented. In Chapter 4, a paper reporting the predictive modeling study of the initial alcohol lapse was presented.

2 Evaluation of a Smartphone-based Patient Monitoring Instrument in Alcohol Addiction

2.1 Abstract

Background: This study examined the psychometric properties of the Weekly Check-in, a smartphone-based, ongoing monitoring instrument for patients with alcohol addiction.

Methods: 170 adult patients who met the criteria for DSM-IV alcohol dependence were recruited from two residential treatment organizations in U.S. from February 2010 to November 2011 and were given the access to the Weekly Check-in as a part of a mobile health system intervention.

The Weekly Check-in items were modified from the Brief Addiction Monitor instrument. The factor structure and reliability of the Weekly Check-in were examined in the factor analyses.

Predictive validity of the discovered factors against the initial, self-reported substance use after inpatient detoxification was examined.

Results: Averagely, patients took 2.78 minutes in their first Weekly Check-in. Two factors were found using exploratory and confirmatory factor analyses. The recovery protection factor included abstinence confidence, the attendance of AA meetings, spiritual activities, other activities, and the time spent with families/friends. The recovery risk factor included sleeping problems, depression, urge, risky situation, and relationship troubles. These two factors showed good reliability and discriminative validity. The protection factor score and the overall recovery progress score (i.e., subtracting the recovery risk factor score from the recovery protection factor

score) were predictive of the initial lapse reported in following Weekly Check-in, with and without controlling for distal risk variables.

Conclusions: The Weekly Check-in, being reliable, theoretically sound, and predictive of the initial lapse within a week of reporting, may help to offer ongoing, adaptive care to patients with addiction.

Keywords: Addiction, Substance abuse, Reliability, Validity, Assessment, mHealth

2.2 Introduction

Extending care beyond traditional, clinic-based treatment is needed for patients who strive to stay sober after inpatient detoxification (McKay, 2009). In order to offer personalized and adaptive care to these patients, it is essential to have the ability to monitor their recovery progress continuously in their own communities (Cacciola et al., 2013; McLellan et al., 2005). Therefore, a valid and reliable instrument administered through a channel that allows for ongoing, remote monitoring is critical.

Mobile communication technology, due to its remote connectivity, increasing popularity, and growing evidence in mitigating health disparity, has shown the potential to offer continuous monitoring and extended care to the patients with substance use disorders (Cohn, Hunter-Reel, Hagman, & Mitchell, 2011; Johnson et al., 2011; Marsch & Ben-Zeev, 2012). Addiction-Comprehensive Health Enhancement Support System (A-CHESS), a smartphone-based application, provides addiction patients a ubiquitous access to a variety of tools designed to improve coping competence, to promote autonomous motivation, and to build support network (Gustafson, Shaw, et al., 2011; McTavish, Chih, Shah, & Gustafson, 2012).

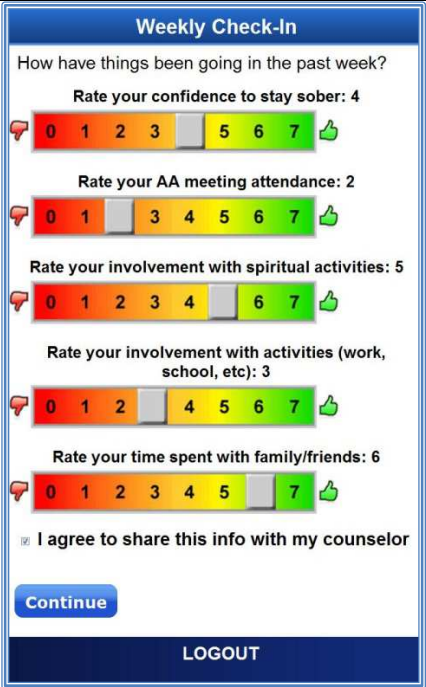
The Weekly Check-in is a patient monitoring tool in A-CHESS. In the Weekly Check-in, patients fill out a brief survey instrument about their recovery status once every 7 days on their smartphones at their preferred time and locations. The Weekly Check-in then transmits the data remotely to a secure server via the mobile wireless Internet. Based on predetermined thresholds and the submitted data in the Weekly Check-in, A-CHESS generates a list of recommended resources and strategies to help patients cope with their situation. The Weekly Check-in data

were also used to develop a Bayesian predictive model that was later implemented in A-CHESS as a lapse prediction system and intervention initiator (Chih et al., 2014). The Weekly Check-in allows patients and their counselors to monitor the longitudinal changes of patients' recovery status. However, no formal evaluation of the Weekly Check-in has been done.

The questions in the Weekly Check-in were adopted and modified from a multi-dimensional instrument, Brief Addiction Monitor (BAM) (Cacciola et al., 2008). Twelve out of the original 17 BAM items were adopted in the Weekly Check-in. Two BAM items about the status of drinking and taking drugs were combined into a single item to assess patients' substance use activities in the past week. These 10 BAM items (i.e., sleeping problems, depression, urge, risky situation, relationship troubles, abstinence confidence, AA meeting, religious activities, other activities, and time with family) that were conceptualized as recovery risks and protection (Cacciola et al., 2008) were adopted in the Weekly Check-in to assess patients' recovery progress and their needs for support. Factors very similar to these 10 protective and risk items outlined above have been found to be strongly associated with substance use behavior (Baker et al., 2004; Hunter-Reel, McCrady, & Hildebrandt, 2009; Laffaye, McKellar, Ilgen, & Moos, 2008; R. H. Moos & Moos, 2007; Oslin, Cary, Slaymaker, Collieran, & Blow, 2009; Robinson, Krentzman, Webb, & Brower, 2011; Witkiewitz & Marlatt, 2004). Two BAM items (i.e., the amount of risky drinking or the types of drugs) were excluded to keep the Weekly Check-in simple. The other three BAM items (i.e., physical health, income, and treatment satisfaction) were excluded because they were less likely to be affected by using A-CHESS.

Moreover, modifications in question wording, scales, and anchors were required in order to adapt the selected BAM items into the Weekly Check-in. The BAM was initially developed to be paper-based and administered at outpatient clinics on a monthly to quarterly basis. Thus, the BAM was designed to cover the last 30 days as the evaluation period (Cacciola et al., 2008). On the other hand, the Weekly Check-in was intended to be used weekly on a smartphone. Therefore, in the Weekly Check-in, the wording of BAM items was changed from “the past 30 days” to “the last 7 days” or “the past week”. Moreover, to increase the readability and usability of the instrument on a 4-inch smartphone screen, the questions were shortened, and the scales were unified to a 0 to 7 scale system using both symbols (thumb up or down) and colors (a color spectrum from green to red) as the anchors. Please refer to Table 2.1 for a side-by-side comparison of the selected BAM items and the corresponding items in the Weekly Check-in.

Table 2.1. The Comparison of Brief Addiction Monitor and A-CHESS Weekly Check-in

Brief Addiction Monitor (Cacciola et al., 2008)		A-CHESS Weekly Check-in
Paper-based written survey		Smartphone touch screen
4. In the past 30 days, how many days did you drink ANY alcohol? __ (0-30) 6. In the past 30 days, how many days did you use any illegal/street drugs or abuse any prescription medications? __ (0-30)		Have you used drugs or alcohol in the last 7 days? ☐ Yes ☒ No
Selected 10 BAM Items	2. In the past 30 days, how many nights did you have trouble falling asleep or staying asleep? __ (0-30)	
	3. In the past 30 days, how many days have you felt depressed, anxious, angry, or very upset throughout most of the day? (0-30)	
	8. In the past 30 days, how much were you bothered by urges to drink alcohol or use drugs? __ Not at all(0) __ Slightly(8) __ Moderately(15) __ Considerably(22) __ Extremely(30)	
	11. In the past 30 days, how many days were you in any situations or with any people that might put you at an increased risk for using alcohol or drugs? (i.e., around risky people, places, or things) __ (0-30)	
	15. In the past 30 days, how much have you been bothered by arguments or problems getting along with any family members or friends? __ Not at all(0) __ Slightly(8) __ Moderately(15) __ Considerably(22) __ Extremely(30)	
	9. How confident are you in your ability to be completely abstinent from alcohol and drugs in the next 30 days? __ Not at all(0) __ Slightly(8) __ Moderately(15) __ Considerably(22) __ Extremely(30)	
	10. In the past 30 days, how many days did you attend self-help meetings like AA or NA to support your recovery? __ (0-30)	
	12. Does your religion or spirituality help support your recovery? __ Not at all(0) __ Slightly(8) __ Moderately(15) __ Considerably(22) __ Extremely(30)	
	13. In the past 30 days, how many days did you spend much of the time at work, school, or doing volunteer work? __ (0-30)	
	16. In the past 30 days, how many days have you spent time with any family members or friends who are supportive of your recovery? __ (0-30)	

Notes:

1. Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System
2. Items 1, 5, 7, 14, and 17 in the original Brief Addiction Monitor were not included in the Weekly Check-in.

In the first evaluation study, the BAM was found to be easily administered (within an average of 6 minutes) (Cacciola et al., 2013). Fifteen BAM items were analyzed in an exploratory factor analysis (EFA) where 11 items were found to constitute three factors. These factors showed good test-retest reliability, good sensitivity to change, and some predictive validity regarding the successful treatment completion (Cacciola et al., 2013). These findings offered the initial psychometric evidence of the BAM. However, the aforementioned changes (i.e. different number of items, item wordings, and scaling) made in the process of adapting BAM into A-CHESS Weekly Check-in have led to a new instrument that needs new psychometric evaluation. In this paper, an evaluation of the Weekly Check-in instrument using data collected in a randomized controlled trial was reported. Specifically, the use of the Weekly Check-in, the factor structure, and the reliability and predictive validity of the scales were reported.

2.3 Methods

2.3.1 Participants

The 170 patients randomized into the intervention group in a randomized controlled trial were included in this study because they were given the access to A-CHESS and the Weekly Check-in (McTavish et al., 2012). Patients were recruited from two residential treatment organizations, one in the Midwestern and the other in the Northeastern U.S., from February 2010 to November

2011. They were at least 18 years old, met the criteria for DSM-IV alcohol dependence when they entered treatment and were able to provide two backup contacts for follow-up. Patients were excluded if they had a history of suicidality, a significant developmental or cognitive impairment that would limit the ability to use A-CHESS, or vision problems. These 170 patients, with a mean age as 38 years old (from 20 to 64), are mostly Caucasians (84%) and mostly male (61%). Only about 8% of patients have a 4-year college degree or higher. Only 20% of patients were employed at the time of enrollment. About 62% of patients have abused drugs.

2.3.2 Procedures

The study was conducted according to the Declaration of Helsinki and approved by the Institutional Review Board at the University of Wisconsin-Madison. On the days when these 170 patients were discharged (i.e., the intervention dates), they each received a smartphone (either Palm Pre or HTC Evo) with a pre-installed A-CHESS and with 3G mobile broadband connection paid up to 8 months after the intervention. The patients agreed and received a prompt in A-CHESS to finish the Weekly Check-in once every 7 days. Using A-CHESS or submitting the Weekly Check-in was not required for patients to stay on study. More details about the randomized controlled trial can be found elsewhere (McTavish et al., 2012).

2.3.3 Weekly Check-in Instrument

The Weekly Check-in contains a three-page instrument (Table 2.1). On the first page (or screen), patients were asked to report their substance use status in the last 7 days in a dichotomized answer (i.e., yes/no). On the second page, they reported their perceived levels of risk-related items (i.e., sleeping problems, depression, urge, risky situation, and relationship troubles) in the

past week in a scale from 0 (thumbs up at the green zone) to 7 (thumbs down at the red zone). On the third screen, they reported their perceived levels of protection-related items (i.e., abstinence confidence, AA meeting, religious activities, other activities, and time with family) in the past week in a scale from 0 (thumbs down at the red zone) to 7 (thumbs up at the green zone). These 10 items were later examined in the factor analyses.

2.3.4 Data Preparation and Analysis

Among 170 patients who received the A-CHESS intervention, 162 completed at least one Weekly Check-in within the 8-month study period. Both EFA and confirmatory factor analysis (CFA) were conducted. To avoid confirming the EFA solution using the same sample, we randomly divided the 162 A-CHESS patients' first Weekly Check-in reports evenly into two datasets—81 reports for EFA and the other 81 reports for CFA. Patients' first Weekly Check-in reports were used in factor analyses to avoid potential carry-over effects caused by repeated testing, i.e., the experiences of completing the first Weekly Check-ins may influence how the second Weekly Check-ins were responded (Keppel & Wickens, 2004).

The time stamp of every click in A-CHESS was sent to a secure server and stored in a log file. Using the log file data, the time spent (in minutes) of the first Weekly Check-in was calculated by subtracting the time when patients clicked the link/icon to start Weekly Check-in from the time when the report was finished and submitted.

2.3.5 Exploratory Factor Analysis

An EFA with the maximum likelihood estimation and a promax rotation method was used to extract the underlying factors of the 10 Weekly Check-in items. A promax rotation is an oblique rotation method allowing correlation between factors. Factor determination was based on the interpretability of the extracted factors, whether the extracted factors match to the literature, and the Kaiser's criterion (i.e., eigenvalues over 1).

2.3.6 Confirmatory Factor Analysis

Comparing to the EFA that was used to explore the potential factor model, a CFA with the maximum likelihood estimation was used to confirm or validate the factor structure discovered in the EFA (Gerbing & Hamilton, 1996). Modification indices were used to further refine the factor model (Kroonenberg & Lewis, 1982). Model fit indices, including Comparative Fit Index (CFI), Tucker-Lewis Index (TLF), root mean squared error of approximation (RMSEA), and standardized root mean squared residual (SRMR), were used to evaluate where the model fit the data well. Cutoffs of Model fit indices for a good fit (CFI > 0.95, TLF > 0.95, RMSEA < 0.06, and SRMR < 0.08) and for a mediocre or acceptable fit (CFI > 0.9, TLF > 0.9, RMSEA < 0.08, and SRMR < 0.08) were used (Bentler, 1990; Hu & Bentler, 1999; MacCallum, Browne, & Sugawara, 1996).

Under the CFA model, the composite reliability and the internal consistency based on Cronbach's alpha were reported. Average variance extracted (AVE)—the average amount of variation that a latent construct (factor) is able to explain in the observed items—was calculated.

Discriminant validity, the extent to which factors are distinct and uncorrelated, is achieved when the squared factor correlations is smaller than AVE (Fornell & Larcker, 1981).

Tau-equivalence and parallelism were examined to ensure that a composite factor score can be reasonably calculated. Tau-equivalence implies that individual items measure the same latent variable on the same scale with the same precision but with possibly different amounts of errors. Parallel models assume that items within the same factor are exactly equivalent to one another and therefore interchangeable (Raykov, 1997). The assumption of tau-equivalence and parallelism were tested by fixing item weights and variances as equal across items, and by comparing a series of nested models with the less restricted model using chi-square difference test (Brown, 2006; Lord & Novick, 1968).

2.3.7 Predictive validity of the Weekly Check-in on the initial lapse

Predictive validity, a kind of criterion-oriented validity (Cronbach & Meehl, 1955), is to examine the predictive relationship between the test (i.e., factors in the Weekly Check-in) and the target criterion behavior (i.e., the lapse status reported in the next Weekly Check-in) (Fig. 2.1). Because the one-item substance use question in the Weekly Check-in asks patients about their substance use status in the last 7 days, in this paper, the “lapse” only indicated whether a patient reported that they drank or took drugs in the prior week and did not provide information about the amount or the frequency of use during the lapse (Chih et al., 2014). If the time between two consecutive reports was more than 14 days, the predictive relation was considered invalid because these two reports were separated by too many days. Therefore, only a Weekly Check-in with a subsequent

Weekly Check-in within 14 days was considered an effective data point. If the next Weekly Check-in reported a lapse, it was taken as such; otherwise, it was considered a non-lapse.

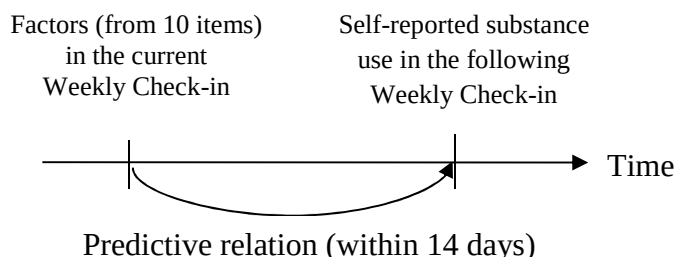


Fig. 2.1. Predictive validity relationship between two consecutive Weekly Check-ins

Besides, on August 17, 2011, a new lapse prediction component was added into A-CHESS (Chih et al., 2014). To avoid the impact of this newly added intervention feature on the predictive relationship studied here, we excluded the data points after August 17, 2011. Based on the above exclusion criteria, 20 patients were excluded from this analysis.

In the remaining 142 patients, 51 had at least one lapse report, their first lapse reports were selected as the positive cases in this analysis. We then randomly selected similar proportions of the non-lapse reports submitted by the other 91 patients to match to the proportions of the lapse cases at different weeks, so that we may avoid the bias from selecting all non-lapse reports submitted at a certain point in time.

Therefore, 142 Weekly Check-in cases were analyzed in logistic regression analyses. The factors from the 10 Weekly Check-in items were predictors. The self-reported substance use status reported in the next Week Check-in was used as the dependent variable in the model. Distal risk factors about treatment, addiction history, comorbidity, social support, and self-efficacy were

found to be related to substance use behavior and therefore used as the controlled variables in this analysis (Donovan, 1996; Hunter-Reel, McCrady, Hildebrandt, & Epstein, 2010; McLellan et al., 1994; Rudolf H Moos & Moos, 2006; Witkiewitz & Marlatt, 2004; Witkiewitz & Masyn, 2008).

2.4 Results

2.4.1 Descriptive Statistics of 162 first Weekly Check-in reports

Within 8 months (or 34 Weeks), 162 patients submitted 3751 Weekly Check-in reports. The average response rate is about 68% of the total possible 5508 (162×34) patient-week. Based on the log file, the average time for 162 patients to finish their first Weekly Check-in is 2.78 minutes with a median at 1.88 minutes and more than 92% of them within 4 minutes. In their first Weekly Check-in, 9 (5.6%) patients indicated that they drank and/or took drugs in the last seven days. The descriptive statistics of the 10 Weekly Check-in items were listed in Table 2.2.

Table 2.2. Item Response Characteristics of the First A-CHESS Weekly Check-in (n=162)

A-CHESS Weekly Check-in Items	Mean	SD	Median	Skewness
1. Rate your difficulty Sleeping (green thumb up(0) – red thumb down(7))	2.47	1.79	2	0.498
2. Rate your level of depression (same as item 1)	2.40	1.85	2	0.701
3. Rate your drinking urges (same as item 1)	1.98	1.76	2	0.978
4. Rate the # of risky situations (same as item 1)	1.92	1.79	2	0.909
5. Rate your relationship troubles (same as item 1)	1.96	1.89	1	0.996
6. Rate your confidence to stay sober (red thumb down(0) – green thumb up(7))	5.65	1.77	6	-1.593
7. Rate your AA meeting attendance (same as item 6)	4.32	2.26	5	-0.474
8. Rate your involvement with spiritual activities (same as item 6)	4.04	2.11	4	-0.279
9. Rate your involvement with activities (work, school, etc.) (same as item 6)	4.17	2.23	4	-0.433
10. Rate your time spent with family/friends (same as item 6)	4.38	2.32	5	-0.564

Note: Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System

2.4.2 Exploratory Factor Analysis

In the EFA and CFA, items 6 to 10 were reversed coded to maintain the same direction for easier interpretation. In the EFA, one- to three-factor models had eigenvalues greater than one (2.930, 2.630, and 1.096 respectively). The three-factor model was not considered as a viable solution because one factor contained only one item. The two-factor model (Table 2.3) matched well to the recovery risk and recovery protection items as conceptualized in the original BAM instrument (Cacciola et al., 2008). The model fit for the two-factor model solution was moderate (RMSEA=0.087 with 90% CI [0.032, 0.134], SRMR=0.065). Factor determinacies, the correlation between the estimated and true factor scores for both factors, were over or near 0.9, showing that the factor scores were well measured (Grice, 2001). A correlation between two factors was weak at 0.045.

Table 2.3. EFA results (n=81)

A-CHESS Weekly Check-in Items	Factor Loadings ¹	
	Recovery Risk	Recovery Protection
1. Rate your difficulty Sleeping	0.347 ²	-0.098
2. Rate your level of depression	0.614	0.198
3. Rate your drinking urges	0.838	0.082
4. Rate the # of risky situations	0.698	-0.087
5. Rate your relationship troubles	0.758	-0.073
6. Rate your confidence to stay sober ³	0.138	0.704
7. Rate your AA meeting attendance ³	-0.014	0.679
8. Rate your involvement with spiritual activities ³	-0.026	0.715
9. Rate your involvement with activities (work, school, etc.) ³	-0.064	0.566
10. Rate your time spent with family/friends ³	0.023	0.613
Factor Determinacy	0.921	0.897

Notes:

1. Maximized likelihood estimation with promax rotation.
2. Bold font shows loadings that were larger than 0.3.
3. Items were reversed coded.
4. Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System

2.4.3 Confirmatory Factor Analysis

The two-factor model was further tested in a CFA using the other half of the data. The resulting model showed a good model fit (RMSEA=0.055 with 90% CI [0, 0.103], CFI=0.956, TLI=0.942, SRMR=0.069). Modification indices showed that no further model improvement was needed.

Standardized loadings were reported in Fig. 2.2.

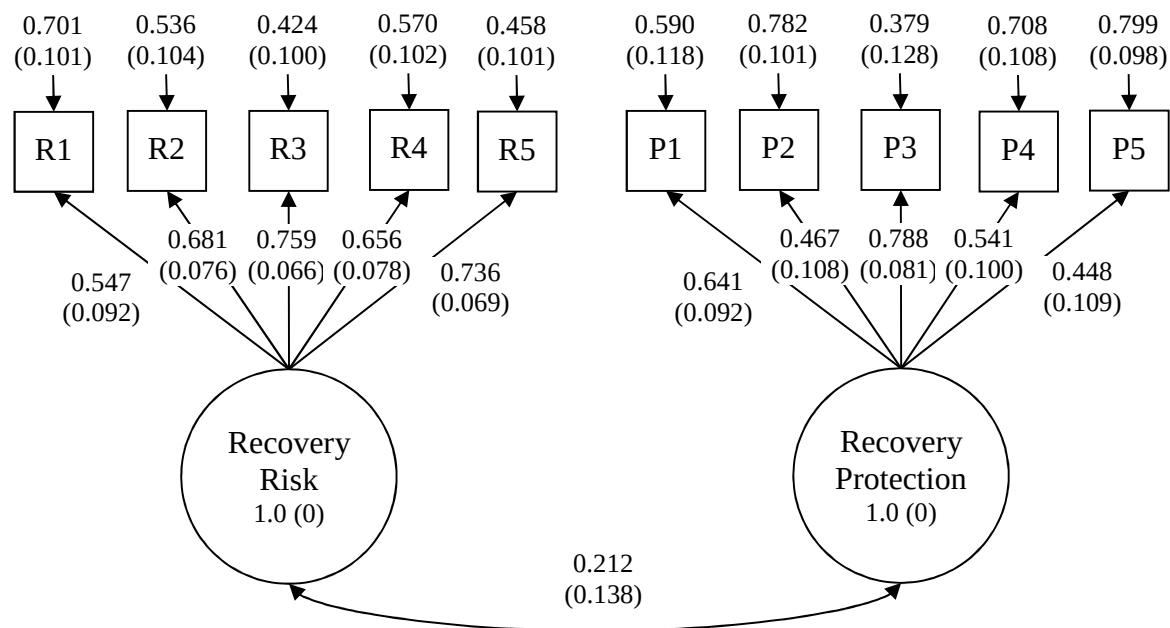


Fig. 2.2. Standardized loadings in CFA

Notes: R1=Difficulty Sleeping; R2=Depression; R3=Drinking urges; R4=Risky situations; R5=Relationship troubles; P1=Confidence; P2=AA meeting; P3=Spiritual activities; P4=Other activities; P5=Time with family. Standard errors are in parentheses.

Composite reliability (0.808, 0.700) and Cronbach's alpha (0.807, 0.692) for the recovery risk and recovery protection factors respectively were over or near 0.7, which showed acceptable reliability (Fornell & Larcker, 1981). Because the AVEs (i.e., 0.460 for the recovery risk factor and 0.325 for the recovery protection factor) were larger than squared factor correlation

$((0.212)^2=0.045)$, discriminant validity was found, showing that these two factors were distinct and uncorrelated from each other (Fornell & Larcker, 1981).

2.4.4 Tau-equivalence and Parallelism

In the first two models with restricted factor loadings, good model fits and the non-significant results of chi-square difference tests between the nested models showed that the model met the assumption of tau-equivalence, which means that the items in the same factors can be equally weighted (Table 2.4). When we further restricted the error variances, only the recovery risk factor showed a sign of parallelism (i.e., the items within a scale are interchangeable), while the recovery protection factor did not meet this assumption. Therefore, a scale score calculated based all items was necessary.

Table 2.4. Tau-equivalence and parallelism nested model comparison (n=81)

	χ^2	Df	χ^2_{diff}	Δdf	p	RMSEA (90% CI)	CFI	TLI	SRMR
Base model (CFA Model)	42.289	34				0.055 (0.000,0.103)	0.956	0.942	0.069
Tau-equivalent: Risk Factor	42.348	37	0.059	3	0.996	0.042 (0.000,0.092)	0.971	0.965	0.069
Tau-equivalent: Both Factors	45.585	40	3.237	3	0.357	0.043 (0.000,0.091)	0.969	0.965	0.075
Parallel: Risk Factor	51.754	44	6.169	4	0.187	0.047 (0.000,0.092)	0.959	0.958	0.084
Parallel: Both Factors	74.545	48	22.791	4	0.001	0.083 (0.043,0.118)	0.858	0.867	0.115

Note: Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System, CFI: Comparative Fit Index, TLI: Tucker-Lewis Index, RMSEA: Root Mean Squared Error of Approximation, and SRMR: Standardized Root Mean Squared Residual

2.4.5 Factor score calculation

Based on the above results, the recovery risk factor score and the recovery protection factor score were calculated by summing the associated item scores, i.e., all items are included and have

equal weights. These two factor scores have values from 0 to 35. Item scores were not reverse-coded. Thus, higher recovery risk factor scores mean higher risks of substance use, and higher recovery protection factor scores mean better protection against the risks. Based on the scoring suggestions in the original BAM instrument (Cacciola et al., 2008), a single factor score, called the overall recovery progress, with a value from -35 to +35, was developed by subtracting the recovery risk factor score from recovery protection factor score.

2.4.6 Predictive validity

Binary logistic regression analyses were conducted on a sample of 142 patients—51 initial lapse cases and 91 non-lapse cases. Six models were evaluated (Table 2.5). Models 4 to 6 have controlled variables in addition to the respective factors included in Models 1 to 3. Overall, regression coefficients of the factors are in the expected directions—higher recovery protection ($p=0.002$), lower recovery risks (although not statistically significant, $p=0.067$), and higher overall recovery progress (i.e., higher recovery protection and/or lower recovery risks, $p=0.002$) may lead to the reduction of the likelihood that patients may lapse within a week of reporting. After controlling for distal risks, the recovery protection and the overall recovery progress remained statistically significant factors (models 4 and 6). The provided odds ratios may be interpreted as such: for example, in model 6, after controlling distal risks, every one unit of increase in the overall recovery progress score may contribute to 4.6% ($1-0.954$) decrease (95% CI [0.922, 0.986]) of the chance of experienced the initial lapse in the following week.

Table 2.5. Predictive validity results (n=142)

	b(SE)	p	OR	95% CI of OR	R ²
Model 1					0.099 ³
Recovery Protection	-0.080(0.026)	0.002	0.923	[0.878,0.971]	
Model 2					0.033
Recovery Risks	0.05(0.027)	0.067	1.051	[0.996,1.108]	
Model 3					0.094
Overall Recovery Progress	-0.050(0.017)	0.002	0.951	[0.920,0.982]	
Model 4 (with distal risks as covariates ^{1,2})					0.171
Recovery Protection	-0.077(0.027)	0.004	0.926	[0.878,0.976]	
Model 5 (with distal risks as covariates)					0.119
Recovery Risks	0.047(0.029)	0.104	1.048	[0.990,1.109]	
Model 6 (with distal risks as covariates)					0.166
Overall Recovery Progress	-0.047(0.017)	0.006	0.954	[0.922,0.986]	

Notes:

1. Covariates include these distal risks items, the number of previous treatments, age starting drinking, age when drinking becomes problems, number of quit attempts, drug use, mental health problems, trauma history, has supporter, living arrangement, high risk taker, and self-efficacy.

2. All covariates were not statistically significant for the model 4 to 6. Model coefficients of covariates were not included in this table but are available upon request.

3. Nagelkerke R Square

4. Abbreviations: SE: standard error, OR: odds ratio, CI: confidence interval

2.5 Discussion

This study reported on an evaluation of the Weekly Check-in, a smartphone-based, patient monitoring instrument for patients with substance use disorders. The factor analyses showed that the Weekly Check-in contains two factors: the recovery risk and the recovery protection factors. These two factors met the assumption of tau-equivalence, and therefore the factor scores were calculated by summing the respective item scores. These two factors showed good reliability and discriminative validity. The recovery protection factor and the overall recovery progress score are predictive of the initial lapse within a week of reporting.

The discovered two-factor model in the Weekly Check-in matched well to the risk and protective items proposed in the original BAM instrument (Cacciola et al., 2008). However, in their initial evaluation, Cacciola et al. (2012) found that 11 out of 15 BAM items loaded on three factors (i.e., recovery protection, physical and psychological problems, and the substance use and risks factors). Compared to the recovery protection factor found in Cacciola et al. (2012), the recovery protection factor found in this study contains one additional item (i.e. other activities). The recovery risk factor in this study contains partial items from the other two items in Cacciola et al. (2012) (i.e., physical and psychological problems, and the substance use and risks factors). We suspected that these differences in the results of factor analyses between this study and Cacciola et al. (2012) were due to: (1) different items and (2) the change of item scales and wordings as described in the Introduction section. For example, one of three items in the physical and psychological problems and two of four items in the substance use and risks factor in the original BAM were not included in the Weekly Check-in.

The Weekly Check-in was found to be brief with a high response rate and usefulness. Given the fact that interruptions may occur when patients filled out the Weekly Check-in on their smartphones in realistic settings, most patients (92%) were still able to finish their first Weekly Check-in within 4 minutes, as compared to 5-10 minutes for the paper-based BAM reported in Cacciola et al. (2012). In the telephone interviews during the trial, the Weekly Check-in was identified by the patients as one of the most helpful features in A-CHESS. A few exemplary comments from patients were listed here: “The weekly surveys make me think.”; “Weekly Survey--keeps those things in my mind on a daily basis so I'm keeping a balance and the

repetition of that is helpful.”; and “It helps me check in weekly - helps me keep track of progress and I feel like I have made a lot of progress in the last 4 months.”

The development of a single score (i.e. the overall recovery progress) among the Weekly Check-in items has important utilities and associated assumptions. According to the original BAM instrument (Cacciola et al., 2008), researchers proposed a single score (calculated by subtracting the summed risk items from summed protection items) for clinicians to provide feedbacks to their patients regarding patients’ recovery progress. However, the same group of researchers did not mention this calculation in their evaluation paper of the BAM (Cacciola et al., 2013). The original proposed single summary score is simple and intuitive. Because the summed risk item score (i.e. recovery risk score) and the summed protection item score (i.e. recovery protection score) are in the same scale (0 to 35) in the Weekly Check-in, when the recovery risk score equals to the recovery protection score, the recovery progress score is zero. When patients have higher protection and lower risk (i.e. recovery protection score higher than the recovery risk score), the recovery progress score is positive, and vice versa. A-CHESS has implemented this single score in a graphical format allowing patients to see their own recovery progress after they finish their Weekly Check-in (Fig. 2.3). Based on the user feedbacks, this single summary score seems to provide an easy-to-understand method to track patients’ recovery progress. However, this score was developed based on a strong assumption which is that these two dimensions—*high* protection *high* risk and *low* protection *low* risk—have a similar impact on the recovery outcome. In a predictive modeling paper (Chih et al., 2014), researchers have found that this recovery progress score offered good predictability of the weekly lapses, which is similar to the finding of predictive validity in the present paper. While the assumption of this score calculation needs to

be further tested, this score has provided a simple yet useful way to track patient's recovery progress.

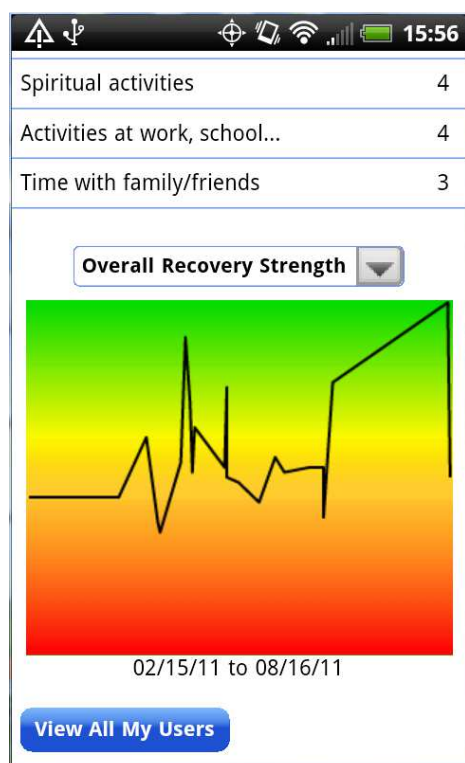


Figure 2.3 Screenshot of the recovery progress score tracking in the Weekly Check-in

The predictive relationships between the factor scores and the initial lapse may have important implications regarding the future development of A-CHESS. For instance, if we know in a week earlier that a patient may drink or take drugs based on their current Weekly Check-in responses, we may be able to develop a new feature in A-CHESS that alerts the counselors and the patients, as well as offers them proactive support to prevent the initial lapse from happening. However, because these results are preliminary, future studies that examine, validate, and apply the

predictive relationships found at the present study may help to make the most use of the Weekly Check-in.

Self-reported substance use outcome may draw concerns about the predictive validity results. Since completing the Weekly Check-in was voluntary, and patients may choose not to share the reported information with their counselors, no salient incentive was present for patients to falsify their substance use status. Moreover, previous studies showed that self-reported substance use is generally reliable and valid, especially when the recall period is shorter (Del Boca & Darkes, 2003), and the responses are collected through technology-assisted methods, e.g., the interactive voice response (IVR) (Del Boca & Darkes, 2003; Perrine, Mundt, Searles, & Lester, 1995). However, further validation of the self-reported substance use item in the Weekly Check-in using objective data sources, like collateral reports from family members/close friends, or clinical measures, is needed.

Two other limitations were related to the data used in this study. First, the data used in factor analyses were from patients' first Weekly Check-in. There were 8 patients who did not fill out any Weekly Check-in. Therefore, their data were not included in the analyses. Similarly selection criteria (e.g. two consecutive Weekly Check-ins) were needed to prepare data for predictive validity analysis. However, patients who did not fill out Weekly Check-in may have some valid and non-ignorable reasons that could be potentially related to their substance use status. For instance, some patients who lapsed might not want to disclose their drinking status in A-CHESS but would tell their counselors at a different setting. This kind of non-random missingness may limit the generalizability of the results. The psychometric properties found in this study may not be applied to all alcohol addiction patients but only to those who would use A-CHESS and

Weekly Check-in. The second limitation is the sample size. We had a modest sample size ($n=162$). In order to complete both EFA and CFA we further divided the sample evenly into half to avoid the fallacy of confirming the found structure using the same sample. In the EFA, a small sample size may still be able to produce reliable results when there was a high variable to factor ratio and high communities (meaning high model fit), which happened to be our case (de Winter, Dodou, & Wieringa, 2009). A good model fit, good reliability, and adequate discriminative validity found in the CFA support that the two-factor model is reliable. However, future evaluation of the Weekly Check-in in larger and/or other populations (e.g., patients with drug addiction) may offer the evidence to confirm the current results.

A valid and reliable patient monitoring instrument is necessary in order to offer high quality, ongoing care to patients with addiction. At the present study, A-CHESS Weekly Check-in was found to be reliable, theoretically sound, and predictive of the initial, near-term lapse after a period of detoxification. Utilizing the power of mobile communication technology, the Weekly Check-in provides an ongoing assessment that could be utilized to offer personalized and adaptive care for patients who desire to stay sober after leaving the inpatient care and returning to their own communities.

3 Exploring the use patterns of a mobile health application for alcohol addiction before the initial lapse after detoxification

3.1 Abstract

Addiction-Comprehensive Health Enhancement System (A-CHESS) is a mobile health intervention that has shown its effectiveness in improving alcohol addiction recovery outcomes in a recent randomized controlled trial (Gustafson et al., 2012). However, less is known about how addiction patients actually used such interventions, especially during the process of quitting addictive behaviors. The purpose of this study is to explore the underlying A-CHESS use patterns of alcohol addiction patients prior to the initial lapses after they left the in-patient treatment programs. 142 patients (51 initial lapsers and 91 non-lapsers) were selected from a randomized controlled trial testing A-CHESS at two treatment agencies in the Northeastern and Midwestern U.S. Comprehensive A-CHESS use measures were developed based on three levels of A-CHESS usage and three categories of A-CHESS services that were designed to support the three psychological needs outlined in the Self-Determination Theory. A latent profile analysis was conducted to uncover the underlying system use patterns based on these A-CHESS measures. Low, medium, and high A-CHESS user profiles were found. Generally, compared to the medium users, high users more actively participated in online social support activities, used more service sessions, viewed more pages, and used A-CHESS longer especially in coping competence and relatedness services. Although the differences of the initial lapses between A-CHESS use profiles were not statistically significant in the present study, several implications in the light of the comprehensive use measurement model and the literature were discussed.

3.2 Introduction

According to a 2011 study, almost nine percent of the U.S. population aged 12 or older were diagnosed with alcohol dependence or abuse (Substance Abuse and Mental Health Services Administration, 2011). One of the major challenges in current alcohol addiction treatment is to extend care beyond traditional in-patient treatment (McKay, 2009). The emerging application of mobile communication and sensor technology in health care (called mHealth) has the potential to complement current treatment approaches in alcohol relapse prevention (Cohn et al., 2011; Gustafson et al., 2005; Marsch & Ben-Zeev, 2012). Preliminary evidence shows that mHealth is well accepted by underserved populations with chronic diseases (including addiction) (McTavish et al., 2012; Rajput et al., 2012). Although mHealth interventions are pervasive, highly accepted, and seemingly effective, less is known about how patients would actually take advantage of mHealth applications, and whether different A-CHESS use patterns may lead to different health outcomes.

Addiction-Comprehensive Health Enhancement Support System (A-CHESS) is a smartphone application developed to support patients with alcohol addiction after they leave residential care. A recent randomized controlled trial showed a significant reduction in the number of risky drinking days for alcohol addiction patients who were given the access to A-CHESS (Gustafson et al., 2012). A-CHESS is designed to offer patients the ubiquitous access to services that are hypothesized to promote the three basic needs outlined by Self-Determination Theory (SDT): autonomous motivation, coping competence, and social relatedness (Gustafson, Shaw, et al., 2011; McTavish et al., 2012; Ryan & Deci, 2000). For example, the alerts and recommendations

in A-CHESS are intended to supplement the impaired cognitive functions of patients by helping them to adopt effective coping strategies when needed. A-CHESS can connect patients to immediate support networks including their addiction counselors, families, and peer patients. Motivational stories and messages from their counselors and peer patients may motivate patients to be on top of their own recovery. The continuous access to services provided in A-CHESS is not available in any existing addiction treatment program, and its use and impact on addiction outcomes is worth exploring.

In the clinical trial mentioned earlier, A-CHESS has been used to predict alcohol lapses. Using patient-reported recovery status in A-CHESS, such as the levels of urge and alcoholics anonymous (AA) meeting attendance, a Bayesian network model was developed to assess the risks of a lapse within a week of reporting (Chih et al., 2014). The model successfully predicts more than 80 percent of the cases. In this model, patients with recent lapse experiences were found to have a high chance of subsequent lapses. In other words, the model can better identify potential lapsed based on whether they have lapsed recently. However, for those who did not lapse previously (i.e., the initial lapse cases), the prediction could be further explored and improved.

A-CHESS use patterns that occurred before initial alcohol lapses may inform the likelihood of such events and make early intervention possible. Previous research has shown that coping activities may reduce the risks of initial lapses (Witkiewitz & Masyn, 2008). The use of A-CHESS can be considered coping behavior. The patterns of A-CHESS use before the initial lapse could potentially offer valuable information to improve initial lapse prediction and prevention.

The purpose of this study is to explore the A-CHESS use patterns before the initial lapse reported by patients who have just completed residential treatment and returned to their own community.

3.2.1 A-CHESS system use patterns

The A-CHESS system creates a log file data that documents a patient's use of the system. System log files contain electronically recorded interactions between the systems and the users (Peters, 1993). Log file analyses provide rich information about how the information and communication technological systems work and how patients may gain benefits from using different components in the systems (Han, 2011). In order to go beyond the traditional log file analysis approach where only the amount of use (e.g., page views) is analyzed, a use-measurement framework that contains different levels of use measurements (i.e., system entry, exposure, and engagement) may help to better understand the use patterns of a multifunctional and comprehensive application, like A-CHESS (Shah, Namkoong, Moon, Chih, & Han, 2011).

In mass media research, system entry is closely related to the notion of selection, meaning that people intentionally choose to allocate their time and attention to mass media, in this case, A-CHESS. System entry means that users choose to turn on the application and therefore can be operationalized as a successful login or session (Shah et al., 2011). Just as a psychosocial and behavioral intervention received by alcohol addiction patients, A-CHESS system entry means that patients choose to attend (open) the treatment (the applications). Choosing to access the treatments may imply stronger motivation of alcohol addiction patients (Cunningham & McCambridge, 2012). Mounting evidence shows that the attendance at treatment sessions, AA

meetings, religious activities, or 12-Step group meetings is significantly related to improved abstinence outcomes (Bonn-Miller, Zvolensky, & Moos, 2011; Robinson et al., 2011).

System exposure refers to how much information is perceived by the users, often operationalized to be either the amount (the number of “pages”) or the degree (the amount of time) of the exposure. As patients browse through more content in A-CHESS, they may feel more informed, more confident, more supported, and more motivated to resist the temptation to lapse.

Researchers have found that patients who attend more treatment sessions are more likely to achieve better outcomes (S J Lash, 1998; Steven J Lash et al., 2007).

System exposure focuses on “what” content is being perceived by patients, while system engagement focuses on the patients’ interactions with the content. A-CHESS patients not only passively receive information but are also actively engaged in various navigation strategies. They actively learn from and communicate with the other patients or providers (or counselors) via the social networking tools. Most importantly, A-CHESS users may choose to engage in using the system for a sustained amount of time. Previous studies have shown that expressing emotional support and empathy in an online environment was related to a reduction of concerns and improved quality of life (Namkoong et al., 2010). Patients who used the systems more continuously (i.e. longer over-time use) reported improved health competence, social support and active participation in health care (Han et al., 2009). For example, Moos and Moos (2007) found that patients with alcohol addiction who participated in AA meetings for a longer time period were more likely to be remitted at all four follow-ups (R. H. Moos & Moos, 2007), and the

participation of social networks has been found to be an important protective factor in the recovery journey of patients with addiction (Hunter-Reel et al., 2010).

Although system entry needs to occur before exposure or engagement can be reasonably measured, and exposure must occur for engagement to be meaningful, these three use measurement levels are not in a continuum (Shah et al., 2011). Since the tools in A-CHESS offer different functions and content that are designed to meet the three SDT needs, the combination of three levels of system use measurement with three SDT classified A-CHESS services may offer a more comprehensive view of A-CHESS use patterns (e.g., entry to relatedness services, exposure to coping competence services, and engagement with autonomy motivation services).

3.2.2 Latent Class Analysis in System Use

A holistic approach is needed to study the effects of A-CHESS system use patterns. By considering multiple use measures simultaneously, we can better understand the impact of the system on patient outcomes. Latent class analysis (LCA) has been increasingly used as an exploratory approach to study the underlying patterns of a set of complex, observed response variables in either dichotomized or continuous scale (Finch & Bronk, 2011). Compared to traditional clustering algorithm, such as k-mean, LCA is a model-based approach that offers cluster solutions that are supported by rigorous statistical tests and based on a mixture of the underlying probability distribution, which makes the solution less arbitrary (Magidson & Vermunt, 2002). Latent profile analysis (LPA), a type of LCA in which all indicators are continuous, has been used in medical research to identify relevant and valid groups in skin cancer risks (Steffen, Glanz, & Wilkens, 2007), youth risky behavior patterns (Cole et al., 2007),

and alcohol dependence and abuse (B. Muthén, 2006). In a recent study of the system use patterns of a web-based eHealth intervention for cancer patients, LCA was proved to be a useful technique to identify subgroups of eHealth system users (Børøsd, Cvancarova, Ekstedt, Moore, & Ruland, 2013). In the present study, because the use measures are continuous, LPA will be used to explore the underlying A-CHESS use patterns based on a comprehensive set of A-CHESS use measures.

In a recent review of various effective behavior interventions for addiction patients, researchers pointed out that the real challenge is to choose the most appropriate treatments for a given patient (Witkiewitz & Marlatt, 2011). The same challenge was faced in the development of various services offered in A-CHESS. Exploring A-CHESS use patterns before the initial lapse may offer important information about which patterns of system use matter in A-CHESS. Ultimately, understanding effective use patterns in A-CHESS may help to design more effective mHealth interventions for addiction patients.

3.3 Methods

3.3.1 Participants

A total of 170 patients were randomized into the intervention group in a randomized controlled trial (McTavish et al., 2012). Among them, 142 patients were included in this study because of inclusion criteria during data cleaning (see section 3.3.5). The intervention group was given the access to A-CHESS; the control cases did not have access to A-CHESS and so are excluded from

this analysis. The patients were recruited from two residential treatment organizations—one in the Midwest and the other in the Northeastern U.S.—from February 2010 to November 2011. They were at least 18 years old, met the criteria for DSM-IV (American Psychiatric Association, 2000) alcohol dependence when they entered treatment, and were able to provide two backup contacts for follow-up. Patients were excluded if they had a history of suicidality, a significant developmental or cognitive impairment that would limit the ability to use A-CHESS, or vision problems.

3.3.2 Procedures

The study was conducted according to the Declaration of Helsinki of 1975 and approved by the Institutional Review Board at the University of Wisconsin-Madison. Patients were recruited at each clinic by project coordinators before they were discharged. Written informed consent was obtained from patients who were willing to participate in the study. Before leaving the facilities, patients received training on how to use A-CHESS and the smartphones from their counselors. On the day when they were discharged (i.e. the intervention date), they each received a smartphone (either Palm Pre or HTC Evo) with a pre-installed A-CHESS program. 3G mobile broadband connection was paid up to 8 months after the intervention dates. The patients agreed to use A-CHESS. However, using A-CHESS is not required for patients to stay on study. The system log data were sent to a secure server at University of Wisconsin-Madison. Further details about the randomized controlled trial can be found elsewhere (McTavish et al., 2012).

3.3.3 Intervention—Services provided in A-CHESS

A-CHESS services were designed to focus on one or more SDT needs.(Gustafson, Shaw, et al., 2011) Detailed information about different A-CHESS services has been reported elsewhere (Gustafson, Boyle, et al., 2011; Gustafson, Shaw, et al., 2011; McTavish et al., 2012). A brief description of A-CHESS services is listed in Table 3.1. The following is a list of services targeting the three SDT constructs

Services for promoting autonomous motivation. High-Risk Locator, Notifications, Recovery Motivation, Panic Button, Weekly Survey, Daily Check-In, Sobriety Date Counter, Our Stories, and Recovery Podcasts.

Services for improving coping competence. Notifications, Panic Button, Discussions, Ask an Expert, News, Easing Distress, Instant Library, Recovery Information, Open Expert, FAQs, Weblinks, Tutorials, Our Stories, and Recovery Podcasts.

Services for building relatedness. Panic Button, Weekly Survey, Daily Check-In, Discussions, Ask an Expert, Events and Meeting Planner, My Friends, My Messages, My Profile, My Team, and Team Feed.

Table 3.1. Services provided in A-CHESS

<i>Discussion Groups</i>	Participants can anonymously exchange emotional support and information with other A-CHESS users via online bulletin-board support groups.
<i>Ask an Expert</i>	Allows A-CHESS users to receive personal responses to their questions from experts in addiction within 48 hours.
<i>Open Expert</i>	Responses to questions sent to Ask an Expert that are of general interest are rendered anonymous and made available for all users to view.
<i>My Team</i>	Participants were grouped into teams based on the recruitment sites. They can see each other contact information and status updates in this service.
<i>My Wall</i>	Through this Facebook like service, participants may see their teammates' updates and other updates like discussion group posting in this service.
<i>My Messages</i>	Participants may send personal messages to other A-CHESS users functioned like e-mails.
<i>A-CHESS Personal Stories</i>	Professionally produced text and video accounts of recovery experiences based on interviews of patients and family members. Stories focus on ways to overcome barriers to addiction management as well as how to make different choices and cope with challenges.
<i>Instant Library</i>	Detailed summaries of articles, chapters, and manuals on addiction management.
<i>Medication Resource</i>	Information about addiction pharmacotherapies, side effects, and ways to reduce barriers to adherence (e.g., forgetting to take medications, daily techniques to remember to take medications).
<i>FAQs</i>	Brief answers to frequently asked questions about addiction, such as "Why do some people become addicted to drugs, while others don't?" and "How do I deal with cravings for alcohol?" Links to additional CHESS services offering more detailed information and support are also provided.
<i>Web Links</i>	Patient's access approved addiction-related web sites (and specific pages within sites).
<i>Easing Distress</i>	A computerized cognitive-behavior therapy program designed to help people cope with harmful thoughts that can stymie efforts to prevent relapse. It helps assess logical errors, attributional style, and the tendency to exaggerate distress, and offers practical exercises to improve cognitive problem-solving skills.
<i>Healthy Events Newsletter</i>	Alerts the person in recovery about healthy drug- and alcohol-free events taking place in their city.
<i>High-Risk Patient Locator</i>	Global positioning system (GPS) technology tracks when participants approach an area where they traditionally obtained or consumed alcohol so they can receive "just-in-time" support to work through what might be a high-risk situation for relapse. To activate, individuals voluntarily register places where they regularly obtained or consumed alcohol in the past and now designate as a high-risk locations for relapse.
<i>Daily Thoughts</i>	Motivational quotes (usually about sobriety) sent via text messaging each morning to A-CHESS participants.
<i>Sobriety Counter</i>	Appears on the home page of A-CHESS to remind participants of how many days they have been sober.
<i>Panic Button</i>	Provides immediate help to avoid an imminent relapse (e.g., if urges and cravings

	become severe and help is desired). By pressing the PANIC BUTTON an intervention (set up during training) would start, including automated reminders to the patient (personal motivations for not drinking), computer-generated alerts to key people (e.g., counselor, sponsor, counselor, family) who may reach out to the patient via phone or in person, and specific tools for dealing with urges.
<i>Weekly Check-In</i>	Brief survey (Brief Alcohol Monitoring Index) to obtain patient data on negative affect, lifestyle balance, and recent substance use. <i>Check-in</i> information is used by A-CHESS for triage and feedback. Patients' care managers are automatically notified if a participant score exceeds a predetermined threshold. The care manager can view a summary report of Check-in data if they wish.

A-CHESS: Addiction-Comprehensive Health Enhancement Support System

3.3.4 Measures

3.3.4.1 Initial Lapse and prediction relationship

The substance use item from the Weekly Check-in was used as the indicator of a patient's initial lapse status. The Weekly Check-in is a self-monitoring service provided in A-CHESS for patients to track their recovery progress (Chih et al., 2014). Patients filled out an online questionnaire in the Weekly Check-in every 7 days in A-CHESS on their smartphones. The status of their self-reported substance use behavior (i.e., drug and alcohol use) in the last 7 days was measured on a dichotomous scale (yes/no). Therefore, a lapse is defined to have occurred when a patient indicated that he/she used alcohol or took drugs in the last 7 days in their Weekly Check-in reports (Chih et al., 2014). Patients may report lapses in multiple Weekly Check-in reports during the 8-month study period. The first reported lapse cases in the Weekly Check-in reports after patients left the treatment facilities were identified as the initial lapse cases.

The lapse status that patients reported in the Weekly Check-in was about their substance use in the last 7 days. If the time between two consecutive Weekly Check-ins was more than 14 days, the prediction was considered invalid because it was separated by too many days from the prior

report (Chih et al., 2014). Therefore, only a current Weekly Check-in with a subsequent Weekly Check-in within 14 days was considered an effective data point. If the next Weekly Check-in reported a lapse, it was taken as such; otherwise, it was considered a non-lapse. The use data that happened between the current Weekly Check-in and the previous Weekly Check-in were retrieved and used to develop measures of pre-lapse A-CHESS use (see Fig. 3.1).

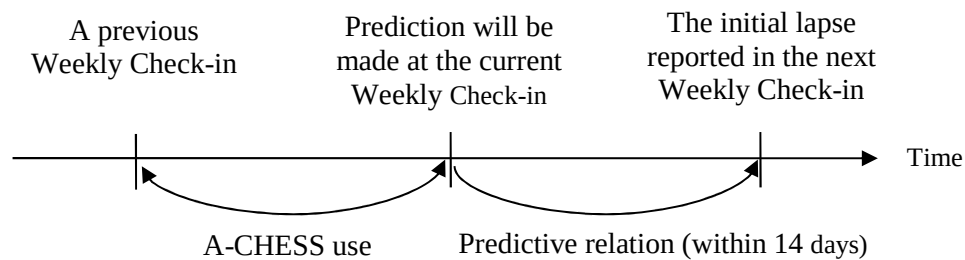


Fig. 3.1 Initial lapse prediction conceptual diagram

3.3.4.2 Use measurements

A-CHESS was configured and programmed to automatically record A-CHESS use data at the level of individual keystrokes or clicks of hyperlinks. The log file contains unique user identifiers and timestamps. Therefore, the log file can reveal precisely who requested what A-CHESS services and when. The log file data can be used to establish the types of activities in which the user was engaged (e.g., posting or reading) as well as the specific services that were requested (e.g., news or discussion group messages) at any time periods when A-CHESS was used.

From the log file data, A-CHESS use metrics were developed based on a combination of the SDT-focused A-CHESS service categories and the three levels of system use: entry, exposure, and engagement (Table 3.2). Different SDT-based A-CHESS services were defined above. The operational meanings of the use measures are listed below.

Average daily sessions as system entry. The average number of daily sessions between the previous and current Weekly Check-in was calculated as the measurement for system entry. A new session is recorded when patients switched from using one service, such as discussion group, to another, such as easing distress.

Average daily pages viewed as system exposure. System exposure could be operationalized by pages viewed or time spent. Compared to those using computer-based applications, smartphone application users were not restricted to a physical location, and therefore, could be more easily distracted by other tasks, like walking and chatting with friends. This could cause time-based exposure measures to be overestimated. In addition, the contents in A-CHESS are often short and simple, and therefore do not require much time to achieve comprehension. Therefore, the duration of time between pages may not be a good measure in the context of a smartphone application. The amount of content (the number of pages viewed) may be a more useful and realistic measure of system exposure. The average number of daily pages viewed between the previous and current Weekly Check-in was calculated as the measure for system exposure.

Percentage of days using A-CHESS as over-time system engagement. Over-time engagement has been used to describe the commitment and the continuous nature of system engagement in other studies (Han et al., 2009; Shah et al., 2011). In this study, the measure of over-time system

engagement was operationalized by dividing the number of days a patient used A-CHESS divided by the total number of days between the patients' previous and the current Weekly Check-in. The scale for this percentage measure is from 0% to 100%.

Average daily posting messages as social engagement. The average number of daily messages posted or sent by patients between the last and the current Weekly Check-in was used to measure social engagement.

Table 3.2. A-CHESS use measurement construction

		All services ¹	A-CHESS services by SDT contents (SDT Services)		
			AM Services	CC Services	RE Services
Measurement	Entry	Total entry	AM entry	CC entry	RE entry
	Exposure	Total exposure	AM exposure	CC exposure	RE exposure
	Over-time engagement	Total over-time engagement	AM over-time engagement	CC over-time engagement	RE over-time engagement
	Social engagement	Total social engagement			

1. Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System; AM: Autonomous motivation; CC: Coping competence; RE: Relatedness

2. All services contain all three SDT services and the homepage.

3.3.5 Data preparation and analysis

The use data retrieval was based on the submission date and time of the selected Weekly Check-in reports. Initial lapse cases were retrieved from the Weekly Check-in database in the process flow below (see Fig. 3.2). In August 2011, a new intervention component was added to provide additional, automatic alerts sent out to both patients and counselors about patients' risk of upcoming lapses. To avoid the impact of the new intervention on the predictive relationship studied here, four patients were excluded because all of their Weekly Check-in reports were submitted after this new intervention feature. Of the remaining patients, six did not have

effective initial prediction data points: that is, a Weekly Check-in followed by a subsequent Weekly Check-in submitted within 14 days. Among 152 patients with effective prediction cases, 58 reported a lapse in at least one report, but 7 of them were excluded because their initial lapse was reported during their first Weekly Check-in—there was no prior Weekly Check-in to be used together as a prediction point. Because the 51 initial lapse cases occurred in different weeks of the 8-month study period, a matching process was performed to select compatible non-lapse cases. The process selected a number of non-lapse reports at a particular time point (e.g., 4th week after intervention) to match to the same proportion of lapse cases reported on the same week. Because all the initial lapse cases happened after the 2nd week of the intervention, 3 patients who only have non-lapse reports before the 2nd week were excluded as not matched non-lapse cases. The final dataset contains 51 lapse cases and 91 non-lapse cases.

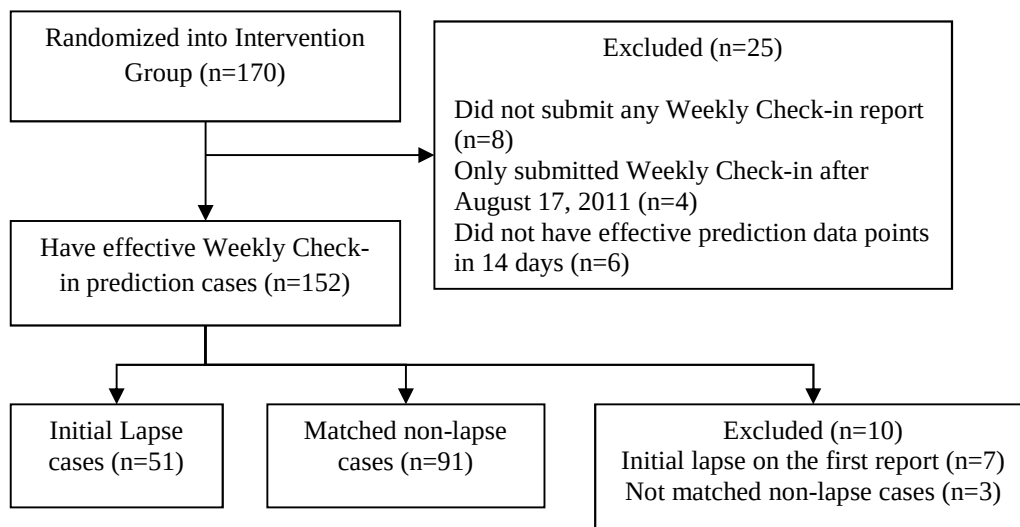


Fig. 3.2 Initial lapse data process flow chart

After selecting these 142 cases (i.e. 51 lapse and 91 matched non-lapse cases), A-CHESS log data between reports (Fig. 1) were retrieved. Usage measures were calculated for each case.

Outliers (with z-score over 3 or below -3) were recoded to the next most extreme values to minimize the impact of outliers (Osborne & Overbay, 2004). Because all use measures are continuous variables, latent profile analysis (LPA) was conducted to identify the underlying A-CHESS use patterns. The initial data cleaning revealed that before initial lapses about 38% of patients did not use coping competence services and about 33% of patients had used any A-CHESS service every day before the initial lapse (i.e. 100% in total over-time engagement measure). Due to the high proportion of subjects at the extreme boundary values, a censored normal distribution was modeled between these variables and the latent profile variables in LPA (L. K. Muthén & Muthén, 2012; Tobin, 1958). LPA was done in the mixture modeling framework using Mplus v7.11.

This LPA identified the underlying use patterns (i.e. latent profiles) based on the comprehensive sets of use measures (Table 3.2). The model solutions were estimated from a model containing only two latent profiles. The model estimation continued by increasing the number of latent profiles until the most parsimonious model solution was found. The most parsimonious model was determined by minimizing Bayesian Information Criteria (BIC), statistically significant results in Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), and entropy (over 0.9) (Nylund, Asparouhov, & Muthén, 2007). During each latent class modeling procedure, a three-step process was adopted to test the predictive relationship between latent profile groups and a distal outcome variable, i.e. the subsequently-reported initial lapse in the following Weekly Check-in. The three-step procedure can avoid the impact of a distal outcome variable (i.e. the initial lapse) on the latent profile groups when considering them in the same model (Asparouhov & Muthén, 2013). The three-step model was implemented in Mplus v7.11 and was used in this study to offer

the pair-wise chi-square test of the probabilities of the initial lapses among the discovered latent classes (Asparouhov & Muthen, 2013).

3.4 Results

A total of 51 initial lapse cases (i.e. lapsers) were reported in the Weekly Check-in. 91 non-lapse Weekly Check-in cases (i.e. non-lapsers) were randomly selected to match to the time schedule when those initial lapses were reported. These 142 patients, had a mean age of 37.93 years old (from 20 to 64), mostly Caucasians (82%) and mostly male (60.6%). About 40% of patients have received some college education or higher. Only 19% of patients are currently employed. About 60% of patients have abused drugs. Table 3.3 shows the descriptive statistics of demographic characteristics and A-CHESS use between those initial lapse cases (lapsers) and those matched non-lapse cases (non-lapsers). Less than 4% outliers ($z > 3$) were found in all use measures except the Total, CC, and RE over-time engagement measures (Table 3.3). From t-tests (for continuous variables) and chi-square tests (for categorical variables), lapsers and non-lapsers were not statistically different on most demographics or any A-CHESS use measures. However, compared to non-lapsers, lapsers are more likely to be female ($p=0.005$) and currently unemployed ($p=0.036$).

Table 3.3. Descriptive statistics of patient characteristics and A-CHESS use

	Lapsers (n=51, 36%)	Non-lapsers (n=91, 64%)	p-value
Demographics			
Age, M(SD)	38.01(9.60)	37.86(9.12)	0.901
Female, N(%)	28(54.9)	28(30.8)	0.005
Race, N(%)			0.895
Caucasian	41(80.4)	73(80.2)	
African American	7(13.7)	11(12.1)	
Other	3(5.9)	7(7.7)	
Education, N(%)			0.248
High school and lower	25(49)	57(62.6)	
Some College	17(33.3)	25(27.5)	
2 and 4 year College degree	8(15.7)	9(9.9)	
Other	1(2)	0(0)	
Drug use, N(%)	33(64.7)	57(62.6)	0.806
Unemployed, N(%)	46(90.2)	69(75.8)	0.036
Use measures			
System Entry (Average daily sessions), M(SD)			
Total Entry	4.01(4.41)	4.30(5.02)	0.731
AM entry	0.29(0.30)	0.27(0.30)	0.746
CC entry	0.73(1.36)	0.70(1.46)	0.919
RE entry	1.72(1.62)	1.83(1.88)	0.719
System exposure (Average daily pages viewed), M(SD)			
Total exposure	13.47(10.17)	14.99(12.93)	0.472
AM exposure	1.93(1.45)	1.77(1.26)	0.499
CC exposure	1.96(2.93)	1.53(2.60)	0.370
RE exposure	9.42(7.32)	9.73(8.96)	0.831
Over-time system engagement (% of days using A-CHESS), M(SD)			
Total over-time engagement	75.37(26.26)	72.86(30.92)	0.625
AM over-time engagement	35.46(16.84)	30.75(14.55)	0.083
CC engagement	26.66(29.59)	23.02(28.59)	0.474
RE engagement	68.38(27.46)	64.70(30.64)	0.477
Total social system engagement (Average daily posting messages), M(SD)			
	0.32(0.43)	0.27(0.43)	0.451

Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System; AM: Autonomous motivation; CC: Coping competence; RE: Relatedness

A latent profile model was developed and estimated. The model contains all use measures outlined in Table 3.2. Model fits indices based on different numbers of profile solutions were listed in Table 3.4. Among these indices, BIC keeps decreasing when models become more

complicated, and all models have good delineation of profiles with high entropy over 0.9.

However, by examining LMR test result, the 3-profile solution was selected because the LMR test showed that the four-level model does not significantly improve the model fit ($p=0.38$).

Table 3.4. Fit statistics of latent profile models

Full model				Decision
Number of Profile	BIC	Entropy	LMR(p)	
2	9286	0.971	0.0452	
3	8943	0.968	0.0244	Selected
4	8760	0.976	0.3849	

Abbreviations: BIC: Bayesian Information Criteria, LMR: Lo-Mendell-Rubin likelihood ratio test.

In Table 3.5, the model estimated profile means were listed to provide an overview of the profile characteristics based on respective use measures. Based on the profile means of the use measures, three profiles can be named as low (35.9%), medium (49.3%), and high users (14.8%). The low users have the lowest A-CHESS use with lower than one service session per day, and 50% over-time system engagement. The medium users have modest A-CHESS use, but their use in several system engagement measures (except for coping competence engagement) approached to those of the high users. Compared to the medium users, the high users have more service sessions, viewed more pages, and used A-CHESS longer especially in coping competence and relatedness services. The high users also more actively posted messages (almost one message a day) via online discussion groups or personal messages, than the medium users (about one message every three days). The high users have the lowest percentage of initial lapsers (28.6%) while the medium users have the highest chances (40.2%) for initial lapse. However, based on the 3-Step model results, the probabilities of the initial lapses between these three groups were not statistically different ($p=0.315$ to 0.691) at the current study.

Table 3.5. Model details

Profiles	Low Users	Medium Users	High Users
% of profile membership counts ¹	35.9%	49.3%	14.8%
% of lapses	33.3%	40.2%	28.6%
Model estimated profile means	System Entry (Average daily session entry)		
	Total	0.817	3.984
	CC	0.214	0.645
	RE	0.387	1.828
	AM	0.139	0.315
	System exposure (Average daily page views)		
	Total	4.218	15.263
	CC	0.372	1.452
	RE	3.007	9.695
	AM	1.255	2.075
	Over time system engagement (% of days using A-CHESS)		
	Total	41.903	90.535
	CC	6.170	24.116
	RE	33.573	81.706
	AM	23.869	35.372
	Online social system engagement (Average daily posting messages)		
	Total	0.052	0.299
		0.888	

Note: 1. The percentage of user counts in profiles are based on the most likely latent profile membership. 2. Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System; AM: Autonomous motivation; CC: Coping competence; RE: Relatedness

3.5 Discussion

The purpose of this study is to explore the underlying use patterns of a mobile health application, A-CHESS, before the initial lapses after a period of inpatient alcohol detoxification. A-CHESS use measures were developed based on three-level system use framework (i.e., system entry, exposure, and engagement), as well as three SDT service categories (i.e., autonomous motivation, coping competence, and relatedness services). In the descriptive statics, the initial lapsers used A-CHESS slightly more than the non-lapsers in most use measures but the differences were not statistically significant. In LPA results, three profiles (i.e. low, medium, and

high users) were found based on a comprehensive list of A-CHESS use measures (Table 3.2). The medium users generally have the highest probability (40.2%) of the initial lapses in the following week while the high users have the lowest probability (28.6%) of such events. However, the probabilities of the initial lapses between these three user profiles were not statistically different in this study.

The non-statistically significant relationships between A-CHESS use profiles and the likelihoods of the initial lapses do not allow for further inferential conclusion to be drawn. However, some results seemingly match to the literature with the potential to explore further and therefore worth mentioning. Compared to the medium users reporting the highest likelihood of the initial lapse, the high users who have the lowest likelihood of the initial lapses also used more service sessions, viewed much more content about coping competence, and actively reached out to others by sending messages. This observation is similar to what was found in the addiction literature where patients who participated more treatment sessions, improved their coping skills, and built stronger support network usually experienced better recovery outcomes (Hunter-Reel et al., 2010; Litt, Kadden, Cooney, & Kabela, 2003; R. H. Moos & Moos, 2007; Rounsaville, 2011; Witkiewitz & Marlatt, 2005). This observation also matches well to a recent publication where researchers found that the patients who used A-CHESS more over an 8-month study period appeared to have fewer risky drinking days (Gustafson, McTavish, & Chih, 2014). Therefore, the high users' A-CHESS use pattern may still be worth promoting, especially for those who consumed fewer coping competence services and less actively participated online social network.

This study has several strengths in both system science and addiction recovery research. The analysis of system use behavior in this study was based on the actual log file data, which represent the objective observation of each activity that patients have with the intervention system, A-CHESS. Therefore, the results in this study were more reliable than self-reported system use. In addition, a comprehensive set of A-CHESS use measures were developed and analyzed together, which offered rich information about the different use patterns among A-CHESS patients before the initial lapses. The A-CHESS use patterns discovered in the LPA, although non-conclusive, seemed to match well with existing addiction literature regarding the impact on the initial lapse. The findings from this study may benefit to the design of A-CHESS-like technological interventions for addiction patients. The method used to study the system use patterns may serve as an example for researchers who develop and test new mHealth interventions for addiction.

Several limitations were related to the data used in this study. First, the data used in this analysis were based on patients' Weekly Check-in. If patients did not fill out Weekly Check-in as described in data preparation section 3.3.5 (e.g. two consecutive Weekly Check-in within 14 days), their data would not be included in the analyses. However, patients who did not fill out Weekly Check-in may have some valid and non-ignorable reasons that could be potentially related to their substance use status. For example, some patients who drank might not want to disclose their drinking status in A-CHESS but would tell their counselors at a different setting. This kind of non-random missingness may limit the generalizability of the results. The latent use profiles found in this study may not be applied to all alcohol addiction patients but only those who would use A-CHESS and Weekly Check-in.

Second, the relative small sample size in this study precluded the construction of a more complex model and may not offer enough power to detect the differences found in this study. The sample population from two treatment agencies was not representative to the general alcohol addiction population. Therefore, future studies should focus on acquiring more participants from more sites. According to a recent PEW research report, adult smartphone owners in the U.S.A. increased from about 30% to 50% in early 2013 (Fox & Duggan, 2012). As mobile communication technology becomes more common, it is more likely to run population-based trial on A-CHESS and similar systems at a lower cost.

Patients who suffer from alcohol addiction need continuous support in order to recover from their addiction. mHealth systems may be an important and useful medium to deliver such interventions. This study offered the understandings of different underlying use patterns of alcohol addiction patients using such interventions and how these patterns are related to the chance of their initial lapse after a period of detoxification in the residential care. Future research in this area to apply and extend the findings in this study is needed in order to develop and refine effective interventions for addiction patients.

4 Predictive modeling of the initial lapse after alcohol detoxification using mHealth

4.1 Abstract

To prevent relapse after residential care, Addiction-Comprehensive Health Enhancement Support System (A-CHESS) was developed to offer ongoing support to patients after they return to the community. This study is to report on a predictive modeling study of the initial lapse submitted by patients using A-CHESS. Predicting the upcoming initial lapse can enable A-CHESS to offer instant and personalized support to patients at the moment. A total of 142 patients recruited from two treatment agencies at the Northeast and Midwest of the U.S.A. Their data collected one time from pretest and ongoing from A-CHESS were included in this study. Based on the literature about the predictors of alcohol lapses, a predictive model consisting of demographics, distal risk factors, and proximal risk factors were developed. The recovery progress score in the A-CHESS Weekly Check-in and the A-CHESS use profiles developed from the A-CHESS use measures were used as proximal risk factors. Two datasets—142 initial lapse cases and 95 second initial lapse cases—were prepared for model development and model testing. Using 142 initial lapse cases, a logistic regression-based model that contains all predictors (called the Full Model) was developed. Through variable selection procedures, a model that contains only two significant predictors (i.e. gender and recovery progress) was also developed (called the Simplified Model). This simplified model showed acceptable predictability in 10-fold cross-validation with the area under receiver operating characteristic curve (AUC) up to 0.69, as compared to 0.55 in the Full Model. However, the Full Model showed better predictability using data from later lapse

episodes, with AUC up to 0.75, as compared to 0.65 in the Simplified Model. Therefore, the Simplified Model may be better applied to new cases, while the Full Model for later lapse episodes. The findings provide an opportunity to improve the accuracy of an existing weekly lapse prediction service provided in A-CHESS. This study may serve as an example in the development and evaluation of new mHealth interventions in the addiction field.

4.2 Introduction

About 9 percent of the US population (aged 12 and older) have been diagnosed as being alcohol dependent or abuse (Substance Abuse and Mental Health Services Administration, 2011). Only about one in every seven patients with alcohol use disorder has received treatments (Cohen, Feinn, Arias, & Kranzler, 2007). Moreover, among those who finished their treatments, up to 80% relapsed to previous drinking behavior within a year (Bradizza et al., 2006; Miller et al., 2001). Innovative addiction treatment programs which are easily accessible, cost-effective, personalized, and offer continuous support for post-treatment recovery are needed (McKay, 2005, 2009).

Mobile health (mHealth) is the use of mobile communication and information technology in health care. Due to the increased computing power, mobile communication capacity, and remote Internet access, mHealth has shown the potential to innovate a wide range of health services, from diagnosis to treatment, from assisting clinicians to supporting patients, from clinical decision making at the moment to chronic disease management (Cohn et al., 2011; Free et al., 2010; Gustafson, Shaw, et al., 2011). With the embedded sensors, like GPS, and the ability to facilitate ongoing data collection, mHealth allows personalized, localized, and instant support to patients (Kumar et al., 2013).

In order to offer just-in-time interventions to support addiction recovery, it is crucial to analyze the data collected via mHealth in the light of the literature regarding the predictive antecedents of substance use behavior (Kumar et al., 2013; McClernon & Roy Choudhury, 2013). This paper presented such a study where a model was developed to predict the initial lapse for those who

just left the residential care and were given the access to a mHealth intervention, called Addiction-Comprehensive Health Enhancement Support System (A-CHESS).

4.2.1 Predictors of alcohol initial lapse

Literature in alcohol addiction research mostly centered on relapse, not the initial and intermediate lapses (Donovan, 1996; Kelly, Hoepfner, Urbanoski, & Slaymaker, 2011; McKay & Weiss, 2001). A lapse is defined, in the present study, as an initial set back(s) while a relapse is a return to previous problematic drinking behavior (Witkiewitz & Marlatt, 2004). In the current movement from the traditional inpatient treatment toward the continuous outpatient approach, researchers called for concurrent monitoring of patients' lapse status weekly or at least monthly in order to offer the instant support to addiction patients (McKay, 2009).

The study of the initial alcohol lapse is important because the initial lapse is strongly predictive of subsequent lapses or relapse (Högström Brandt et al., 1999; Rounsaville, 2011; Witkiewitz & Masyn, 2008; Witkiewitz, 2011). The resulting guilt and negative mood from self-blaming for the initial lapse may likely cause heavy drinking behavior as an escape (Baker et al., 2004; Larimer et al., 1999; Witkiewitz & Marlatt, 2004). In other words, preventing the initial lapse from happening may prevent subsequent lapses or relapse, and help patients recover sooner and better.

Many factors including demographics were found to be related to alcohol lapses. For example, female patients were found to have a higher chance of relapse (Bottlender & Soyka, 2005). Patients who are older, with higher education, or social resources were found to be more likely to obtain a 3-year remission (Rudolf H Moos & Moos, 2006). Besides demographics, the other

factors can be divided into distal or proximal factors according to their temporary nature. Distal factors are distant, individual background factors that define a “set point” or an initial threshold for substance use behaviors to happen (Witkiewitz & Marlatt, 2004). The occurrences of addictive behavior is largely determined by proximal or so-called transient personal responses or contextual influences that may change from time to time (Hendershot, Witkiewitz, George, & Marlatt, 2011; Hufford, Witkiewitz, Shields, Kodya, & Caruso, 2003; Witkiewitz & Marlatt, 2004). However, there is no presumption of whether distal or proximal factors are more influential than the other (Witkiewitz & Marlatt, 2004). They both help to understand the complex, multidimensional, often contextualized nature of alcohol relapsing processes (McLellan, Cacciola, Alterman, Rikoon, & Carise, 2006; Witkiewitz & Marlatt, 2004).

Distal factors are individual backgrounds including broad categories like alcohol or other substance dependence, family history/genetics of alcoholism, personalities, social support, comorbid psychopathology, and physical withdrawal (Donovan, 1996; Hendershot et al., 2011; Witkiewitz & Marlatt, 2004). Compared to those with lower alcohol dependence, patients with higher alcohol dependence, such as previous quitting attempts, were found to lapse earlier and drink more frequently and heavily (Witkiewitz & Masyn, 2008). More previous treatment episodes, longer years of alcohol use, higher severity of drug use, higher psychiatric severity, and more employment issues assessed at the admission were found to be associated with substance use in six months after alcohol rehabilitation treatment (McLellan et al., 1994). Other distal factors (e.g. age starting drinking) and personalities (e.g., impulsiveness and risk-taking) also appear to be different between those with alcohol dependence versus those without (Donovan, 1996). Researchers found that patients with mental illnesses, like depression and bipolar

disorders, are more likely to be alcohol dependent (Bradizza et al., 2006). Another recent study showed that patients with severe mental illness were more likely to skip out-treatment or self-help treatment sessions (Bradizza et al., 2009), and therefore relapse. Regarding social support, researchers found that social support for drinking or not drinking at baseline are strongly related to drinking frequency 6 months after treatment (Hunter-Reel et al., 2010).

Proximal factors include cognitive processes, affective state, and coping behavior (Shiffman, 1989; Witkiewitz & Marlatt, 2004). Cognitive processes, especially self-efficacy and urge, have been widely studied in alcohol addiction research. Self-efficacy or confidence to remain sober has been found to be predictive of relapse (Witkiewitz & Marlatt, 2004). People with higher craving usually experienced higher negative mood and therefore lapsed earlier (Oslin et al., 2009). Cognitive and physical issues including difficulties to concentrate, sleep disturbances, body ache, and urge, as well as negative affect such as frustration and sadness, interpersonal issues such as conflicts with family members and friends, were reported as reasons for initial and subsequent use (Agrawal, Lal, & Chandra, 2009). Being involved in high risk situations, no matter voluntary or not, has been shown to increase the chances of alcohol lapses after a period of abstinence (Rounsaville, 2011). Post-treatment coping behavior was found to be a strong predictor of initial and subsequent lapses (Witkiewitz & Masyn, 2008). Rounsaville (2011) found that patients who more actively engage with recovery activities had more abstinent days and less likely to have initial lapse. An important coping activity, the participation of religious activities, was found to be related to improved self-efficacy and predictive of abstinence (Mason, Deane, Kelly, & Crowe, 2009; Robinson et al., 2011). Patients with social support had fewer drinking

days and fewer drinking-related problems at the end of the treatment (Hunter-Reel, Witkiewitz, & Zweben, 2012).

4.2.2 Predictors of the initial lapse in A-CHESS

Data regularly collected in A-CHESS may serve as proximal factors. The Weekly Check-in, filled out by patients every 7 days, is an ongoing monitoring service in A-CHESS. In the Weekly Check-in, 10 items were designed to measure the proximal factors like abstinence confidence and urge. These items were found to constitute two factors, the recovery protection and recovery risk factors. An overall recovery progress score can be calculated by subtracting recovery risk from recovery protection factor score. In a psychometric evaluation study, the overall recovery progress score was found to be predictive of the initial lapses (Chih, 2013a).

The A-CHESS use is an important proximal risk factor. The use of A-CHESS is like the coping behavior. Via A-CHESS, patients may receive online consultation, collecting with their support network, monitoring their recovery progress, and even doing exercises to ease their distress and urge. Choosing to use A-CHESS services, the amount of content that were consumed, and the frequency and duration may be related to the likelihood of the initial lapse. In a recent A-CHESS use study, a comprehensive list of use measurements was developed based on a system use measure framework (Shah et al., 2011). Using the latent profile analysis, three underlying use patterns (or profiles) were found just one week prior the initial lapses reported by alcohol addiction patients who used A-CHESS (Chih, 2013b). Compared to those who have lower probability of the initial lapse, those patients with a higher probability of such event seem to use coping competence services much less, and also read less content in other services (Chih,

2013b). These patterns warrant further exploration of use patterns in a comprehensive model of the initial lapse prediction.

Based on previous literature in alcohol addiction and recent studies using data in A-CHESS, the present study considered these four major categories of predictors (i.e. demographics, distal factors, and proximal factors from the Weekly Check-in, and from the use measures). The goal of this study is to develop a model with high predictability of the initial lapse, and therefore can be further implemented in A-CHESS as a prediction system. Finding statistically significant predictors is not the focus of this study but could be obtained during the modeling process.

4.3 Methods

4.3.1 Participants

The data used in this study were from a randomized controlled trial testing A-CHESS. The patients were recruited from two residential treatment organizations—one in the Midwest and the other in the Northeastern U.S.—from February 2010 to November 2011. They were at least 18 years old, met the criteria for DSM-IV(American Psychiatric Association, 2000) alcohol dependence when they entered treatment, and were able to provide two backup contacts for follow-up. Patients were excluded if they had a history of suicidality, a significant developmental or cognitive impairment that would limit the ability to use A-CHESS, or vision problems. In this trial, the Intervention group was given the access to A-CHESS, while the control cases, who did not have access to the A-CHESS, are excluded from this analysis. A total of 170 patients were

randomized into the intervention group (McTavish et al., 2012). Among them, 142 patients were included in this study based on the inclusion criteria described in section 4.3.4.

4.3.2 Procedures in the Randomized Trial

The study was conducted according to the Declaration of Helsinki of 1975 and approved by the Institutional Review Board at the University of Wisconsin-Madison. Patients were recruited at each clinic by project coordinators before they were discharged. If the patient was willing to take part, written informed consent and pretest survey about demographics and distal risk factors were then obtained. Before leaving the facilities, patients received training on how to use A-CHESS and the smartphones from their counselors. On the day when they were discharged (i.e. the intervention date), they each received a smartphone (either Palm Pre or HTC Evo) with a pre-installed A-CHESS program. 3G mobile broadband connection was paid up to 8 months after the intervention dates. The patients agreed to use A-CHESS. However, using A-CHESS or completing the Weekly Check-in is not required for patients to stay on study. More details about the randomized controlled trial can be found elsewhere (McTavish et al., 2012).

4.3.3 Measures

4.3.3.1 Initial Lapse and prediction relationship

The substance use item from the Weekly Check-in was used as the indicator of a patient's initial lapse status. The Weekly Check-in is a self-monitoring service provided in A-CHESS for patients to track their recovery progress (Chih et al., 2014). Patients filled out an online questionnaire in the Weekly Check-in every 7 days in A-CHESS on their smartphones. The

status of their self-reported substance use behavior (i.e. drug and alcohol use) in the last 7 days was measured in a dichotomous scale (yes/no). Therefore, a lapse is defined to have occurred when a patient indicated that he/she used alcohol or took drugs in the last 7 days in their Weekly Check-in reports (Chih et al., 2014). Patients may report lapses in several Weekly Check-in reports during the study period. The first reported lapse cases in the Weekly Check-in reports after patients left the treatment facilities were identified as the initial lapse cases.

The lapse status that the patients reported in the Weekly Check-in was about their substance use in the last 7 days. If the time between two consecutive Weekly Check-ins was more than 14 day, the prediction relationship was considered invalid because the two reports were separated by too many days (Chih et al., 2014). Therefore, only a current Weekly Check-in with a subsequent Weekly Check-in within 14 days was considered an effective data point. If the next Weekly Check-in reported a lapse, it was taken as such; otherwise, it was considered a non-lapse. The use data that happened between the current Weekly Check-in and the previous Weekly Check-in were retrieved and used to develop use measures before the lapse events (see Fig. 4.1).

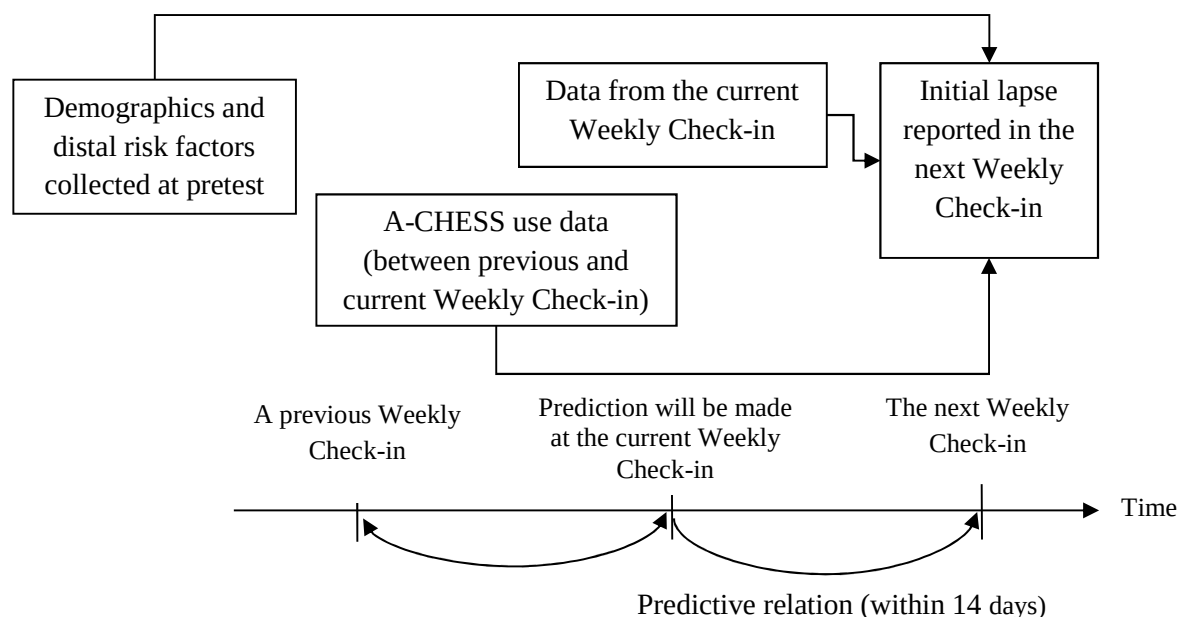


Fig. 4.1 Initial lapse prediction conceptual diagram

4.3.3.2 Predictors

Demographic predictors included gender, education, race, and age, and collected at pretest.

Distal factors include these 6 yes/no dichotomous items: “Drug use—Do you use/abuse other drugs besides alcohol?”, “Mental health issue—Do you have any other mental health problems or issues?”, “Trauma history—Do you have a history of any kind of emotional or physical trauma that still continues to affect you?”, “Has supporter—Do you have at least one person that you can turn to for support?”, “Risk taker—Are you a high risk taker?”, and “Employed—Are you currently employed or self-employed?”. Distal factors also include these continuous items: “Treatment history—How many times have you been to treatment before this time?”, “Age starts drinking—At what age did you start drinking?”, “Drinking becomes problems—At what age did

drinking become a problem for you?”, “Sobriety chance—What do you estimate your chances are (0 to 100) of achieving sobriety?”, “Drinking quit attempts—About how many times have you made a serious attempt to quit drinking?”. This distal factor, “Living arrangement—Where will you be living when you leave treatment?”, is a nominal variable with answers as living alone, living with families or friends, living in a shelter. Two dummy variables were created for this variable as “living alone” and “living in shelter”.

The Weekly Check-in contains a three-page instrument. On the first page (or screen), patients were asked to report their substance use status in the last 7 days in a dichotomous answer (i.e., yes/no). On the second page, patients reported their perceived levels of risk related items (i.e., sleeping problems, depression, urge, risky situation, and relationship troubles) in the past week in a scale from 0 (least) to 7 (most). On the third screen, patients reported their perceived levels of protection related items (i.e., abstinence confidence, AA meeting, religious activities, other activities, and time with family) in the past week in a scale from 0 (least) to 7 (most). The overall recovery progress score was calculated by subtracting the recovery risk factor score (i.e. the sum of the five risk items on the second page) from the recovery protection factor score (i.e. the sum of the five protection items on the third page). These factors have good reliability with Cronbach’s alpha as 0.796 for the recovery risk factor and 0.766 for the recovery protection factor (Chih, 2013a).

A-CHESS was programmed to automatically record usage data at the level of individual keystrokes or clicks of hyperlinks. The log file contains unique user identifiers and timestamps. Using the log file, a matrix of use measures was developed based on the types of measures for

the types of services (see Table 4.1). The services provided in A-CHESS were designed to promote autonomous motivation, coping competence, and social relatedness, the three tenets in the Self-Determination Theory (SDT). More details about the services in A-CHESS can be seen in elsewhere (McTavish et al., 2012). Brief definitions of the types of measurements were listed below.

Table 4.1. A-CHESS use measurement construction

		All services ¹	A-CHESS services by SDT contents (SDT Services)		
			AM Services	CC Services	RE Services
Types of Measurements	Entry	Total entry	AM entry	CC entry	RE entry
	Exposure	Total exposure	AM exposure	CC exposure	RE exposure
	Over-time engagement	Total over-time engagement	AM over-time engagement	CC over-time engagement	RE over-time engagement
	Social engagement	Total social engagement			

Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System; AM: Autonomous motivation; CC: Coping competence; RE: Relatedness

1. All services contain all three SDT services and the homepage.

System entry. The average number of daily sessions between the last and current Weekly Check-in was calculated as the measurement for system entry. A new session is recorded when patients switched from using one service, such as discussion group, to another, such as easing distress.

System exposure. The average number of daily pages viewed between the last and current Weekly Check-in was calculated as the measure for system exposure between the last and the current Weekly Check-in.

Over-time system engagement. The measure of over-time system engagement was operationalized by dividing the number of days when patient used A-CHESS divided by the total number of days between the last and the current Weekly Check-in. The scale for percentage measure is from 0% to 100%.

Social engagement. The average number of daily messages posted or sent by patients between the last and the current Weekly Check-in was used to measure social engagement.

In a recent study using the latent profile analysis, the researcher was able to find three underlying use patterns before the initial lapse cases (Chih, 2013b). The latent profiles were low (35.9%), medium (49.3%), and high users (14.8%). These latent profiles were developed based a set of A-CHESS use measures (Table 4.1). However, Chih (2013b) found that the latent profiles of A-CHESS use were not a statistically significant predictor of the lapse status. Therefore, the latent profiles may not offer good predictability. The individual use measures were later used to replace the latent profiles in a sensitivity analysis to offer a comparison.

4.3.4 Data Preparation and analysis

The data retrieval was based on the submission date and time of the selected Weekly Check-in reports and their prior and subsequent reports. Initial lapse cases were retrieved from the Weekly Check-in database in the following process flow (see Fig. 4.2). In August 2011, a new intervention component was added to provide additional, automatic alerts sent out to both patients and counselors about patients' risk of upcoming lapses. To avoid the impact of the new intervention on the predictive relationship studied here, four patients were excluded because all of their Weekly Check-in reports were submitted after this new intervention feature. Among the rest, six patients did not have effective initial prediction data points: that is a Weekly Check-in followed by a subsequent Weekly Check-in submitted within 14 days. Among 152 patients with effective prediction cases, 58 have reported a lapse in at least one report, but 7 of them were excluded because their initial lapse was reported in their first Weekly Check-in—there was no

prior Weekly Check-in to be used together as an effective prediction data point. Because 51 initial lapse cases happen at different points in time along their 8-month study period, to select compatible non-lapse cases, a matching process was performed. The process selected a number of non-lapse reports at a particular time point (e.g., 4th week after intervention) to match to the same proportion of lapse cases reported on the same week. Because the first initial lapse cases happened after the 2nd week after the intervention, 3 patients who only have effective non-lapse reports within 2 weeks after intervention were excluded. The final dataset contains 51 lapse cases and 91 non-lapse cases. These data were used to develop the predictive model in the model development stage.

Another dataset was prepared for model testing. A two-week abstinence period was used in the literature to separate alcohol lapse episodes (Rounsaville, 2011; Stout, 2000; Zywiak et al., 2006). Therefore, the beginning of the second lapse episode could be treated as an initial lapse. The same data cleaning procedure was used to select the initial lapse cases in the second lapse episode (or called the second initial lapses) for model testing. 17 participants' second lapse episodes were identified, and the Weekly Check-ins reporting their second initial lapses were retrieved. 78 non-lapse cases were matched to the time when the second initial lapse cases occurred (Fig. 4.2).

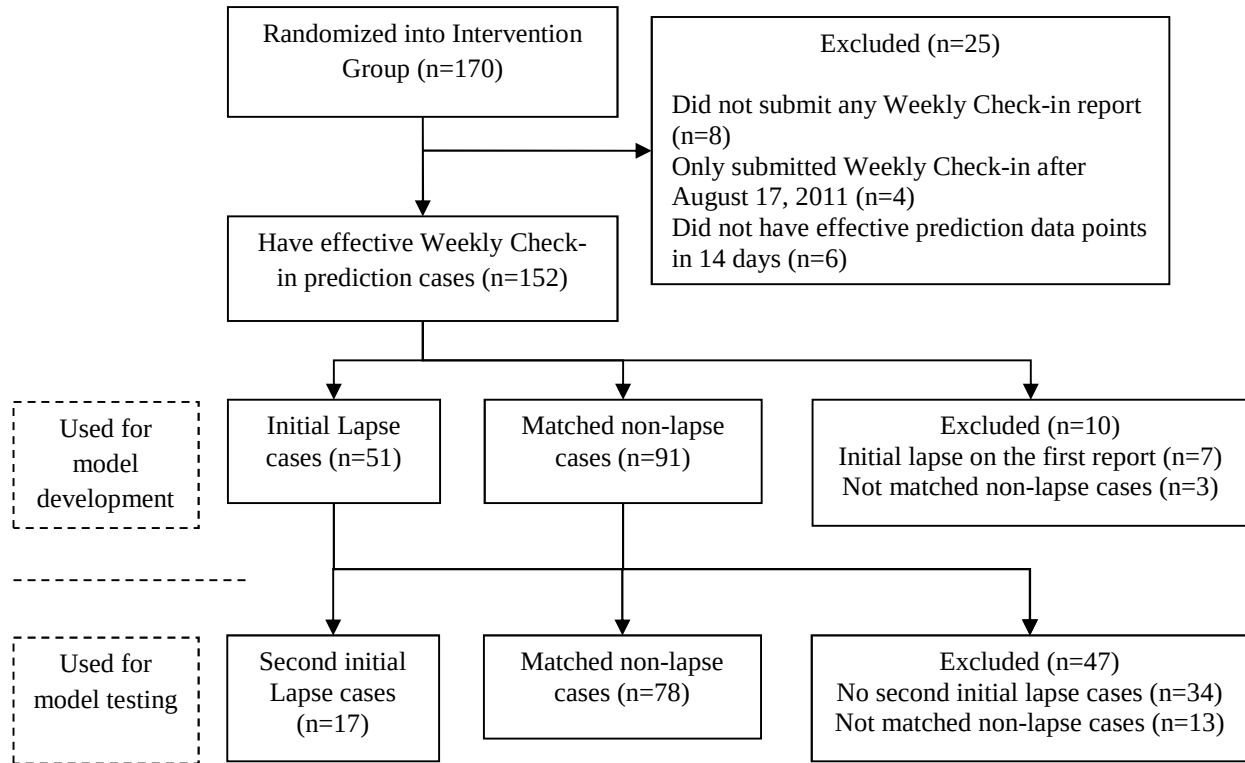


Fig. 4.2 Initial lapse data process flow chart

After preparing the datasets, the recovery progress scores and the A-CHESS use measures were calculated for each case. A logistic regression model was used to develop the predictive model (Fig. 4.1). The Best Subset procedure, a variable selection method, was used in logistic regression models to explore whether certain combinations of independent variables were the optimal predictors (Hosmer, Jovanovic, & Lemeshow, 1989; King, 2003; Lindsey & Sheather, 2010). Factor parameters from the logistic regression model were reported. The predictive probabilities (p_i) of the initial lapse for each patient can then be calculated using the following formulas.

$$y_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_m x_{m,i}$$

$$p_i = \frac{e^{y_i}}{1 + e^{y_i}}$$

In the model development stage, a stratified, 10-fold cross-validation method was used to evaluate the model prediction performance on the datasets that were not used to develop the model (Witten, Frank, & Hall, 2011). In this method, the data were randomly divided into 10 equal-sized subsets. A stratified selection method was implemented to ensure that the proportions of the initial lapse cases were similar between subsets. After 10 subsets were prepared, 9 of them were used to develop a logistic regression model which was then used to estimate the probabilities of the initial lapse for those cases in the one subset that was left out. This model development/testing process were repeated 10 times until the probabilities of the initial lapses in all 10 subsets were estimated. These probabilities were then pooled together and analyzed in the receiver operating characteristic (ROC) curve analysis where these predicted probabilities were compared to the actual lapse status reported in the following Weekly Check-in. The area under the ROC curve (AUC) was used to measure the model predictability (Bradley, 1997). With an AUC value of 1 indicating perfect prediction, an AUC of over 0.7 indicates that a model offers good prediction (Swets, 1988). Final model parameters were developed by using all data in the data development stage.

In the model testing stage using data in the second lapse episode, the model developed in the prior step was evaluated for its predictability of the initial lapses in the later episodes. The AUC analysis results were reported.

Three alternative models were developed using the two datasets for sensitivity analyses. The comparison of predictability between models in the sensitivity analysis was done by comparing the AUCs. The comparisons of the AUCs were done in Stata 13. Other analyses and data preparation were done using SPSS 21.

4.4 Results

Descriptive statistics of the predictors between the initial lapsers and the matched non-lapsers were listed in Table 4.2. Overall, these 142 patients, with the average as 38 years old (from 20 to 64), are mostly Caucasians (80%) and mostly male (61%). The median education level of these 142 patients falls between high school diploma and some college. Only 19% of patients are currently employed. About 63% of patients have abused drugs. Compared to non-lapsers, the initial lapsers are more likely to be female, unemployed, with higher education and previous physical or emotional trauma, and have a lower overall recovery score. Compared to the 142 initial lapse cases (for model development), the 95 second initial lapse cases (for model testing), generally have lower A-CHESS use. Moreover, the lapsers in the second lapse episode have lower A-CHESS use than the non-lapsers although the initial lapsers' A-CHESS use are pretty comparable to the non-lapsers.

Table 4.2. Descriptive statistics of predictors

	Model development (initial lapses) (n=142)			Model validation (second initial lapses) (n=95)		
	Lapsers (n=51, 36%)	Non-lapsers (n=91, 64%)	p ¹	Lapsers (n=17, 18%)	Non-lapsers (n=78, 82%)	p
<u>Demographics</u>						
Age, M(SD)	38.01(9.60)	37.86(9.12)	0.903	39.8(10.34)	38.42(8.96)	0.610
Female, N(%) *	28(54.9)	28(30.8)	0.005	8(47.1)	27(34.6)	0.335
Race, N(%)						
Caucasian	41(80.4)	73(80.2)	0.980	13(76.5)	62(79.5)	0.782
African American	7(13.7)	11(12.1)	0.778	2(11.8)	9(11.5)	0.979
Hispanic	3(5.9)	7(7.7)	0.644	1(5.9)	3(3.8)	0.705
Education, M(SD)	3.57(1.3)	3.22(1.15)	0.114	4.18(1.38)	3.12(1.11)	0.008
<u>Distal Risks</u>						
Dichotomized factors (yes/no), N(%)						
Drug use	33(64.7)	57(62.6)	0.806	8(47.1)	49(62.8)	0.229
Unemployed	46(90.2)	69(75.8)	0.036	15(88.2)	59(75.6)	0.257
Mental health issue	36(51)	43(47.3)	0.670	7(41.2)	39(50)	0.509
Trauma history	31(60.8)	41(45.1)	0.072	12(70.6)	39(50)	0.123
Has supporter	50(98)	87(95.6)	0.450	17(100)	74(94.9)	0.340
Risk taker	30(58.8)	55(60.4)	0.851	13(76.5)	45(59)	0.178
Will live alone	6(11.8)	10(11)	0.888	3(17.6)	8(10.3)	0.388
Will live in shelter	17(33.3)	36(39.6)	0.462	5(29.4)	32(41)	0.374
Continuous factors, M(SD)						
Drinking quit attempts	11.12(50.67)	11.23(20.71)	0.988	26(87.41)	11.29(21.29)	0.500
Treatment history	4.88(9)	3.6(4.76)	0.349	5.82(12.37)	3.13(3.39)	0.388
Age starts drinking	15.27(5.66)	14.45(3.64)	0.352	16.82(7.99)	14.69(3.65)	0.297
Age when drinking becomes problems	22.39(9.99)	20.96(6.88)	0.364	21.47(8.90)	21.36(7.18)	0.962
Sobriety chance	84.04(15.8)	80.89(17.27)	0.273	85.06(14.56)	80.55(17.74)	0.277
<u>Proximal Risks</u>						
Overall recovery progress	8.82(11.2)	15.12(11.19)	0.002	10.12(10.90)	15.56(11.93)	0.078
Use measures						
Latent profiles			0.563			0.123
Low users	17(33.3)	34(37.4)		17(100)	62(79.5)	
Medium users	28(54.9)	42(46.2)		0(0)	11(14.1)	
High users	6(11.8)	15(16.5)		0(0)	5(6.4)	
System Entry (Average daily session entry), M(SD)						
Total Entry	4.01(4.41)	4.30(5.02)	0.731	2.04(1.04)	3.17(3.95)	0.031
AM entry	0.29(0.30)	0.27(0.30)	0.746	0.21(0.10)	0.24(0.27)	0.332
CC entry	0.73(1.36)	0.70(1.46)	0.917	0.16(0.16)	0.44(0.85)	0.003
RE entry	1.72(1.62)	1.83(1.88)	0.708	0.96(0.48)	1.55(1.66)	0.009
System exposure (Average daily page views), M(SD)						
Total exposure	13.47(10.17)	14.99(12.93)	0.472	7.7(3.69)	13.36(10.55)	0.001
AM exposure	1.93(1.45)	1.77(1.26)	0.516	1.78(0.83)	1.80(1.51)	0.959
CC exposure	1.96(2.93)	1.53(2.60)	0.387	0.35(0.52)	1.31(2.53)	0.183
RE exposure	9.42(7.32)	9.73(8.96)	0.821	5.60(2.73)	8.74(7.19)	0.004

Over-time system engagement (% of days using A-CHESS), M(SD)						
Total over-time engagement	75.37(26.26)	72.86(30.92)	0.625	66.61(26.82)	75.52(28.49)	0.232
AM over-time engagement	35.46(16.84)	30.75(14.55)	0.097	31.80(10.72)	31.60(17.92)	0.951
CC engagement	26.66(29.59)	23.02(28.59)	0.478	12.79(11.34)	18.41(27.75)	0.183
RE engagement	68.38(27.46)	64.70(30.64)	0.463	60.98(24.06)	65.13(28.45)	0.539
Total social system engagement (Average daily posting messages), M(SD)						
	0.32(0.43)	0.27(0.43)	0.450	0.11(0.20)	0.23(0.43)	0.068

Notes: 1. For continuous variables, the p values that do not assume equal variances were reported; for categorical variables, the p values in Pearson Chi-square test were reported. 2. Abbreviation: A-CHESS: Addiction-Comprehensive Health Enhancement Support System; AM: Autonomous motivation; CC: Coping competence; RE: Relatedness

4.4.1 Model development

Among all the predictors used in the Full Model, the best sub-set variable selection method showed that gender and recovery progress were the only predictors that mattered. Adding other predictors improved neither the model fits nor predictability. Therefore, a Simplified Model that included only gender and recovery progress was developed as a competing model to the Full Model. The pooled results from the 10-fold cross-validation were analyzed using ROC analyses. Compared to the Full Model (AUC=0.548, 95%CI[0.449,0.647], the Simplified Model showed better predictability with larger ($p=0.002$) area under the ROC curve (AUC=0.686, 95%CI[0.597,0.775]) (Fig. 4.3). Therefore, the Simplified Model is more generalizable to new cases than the Full Model.

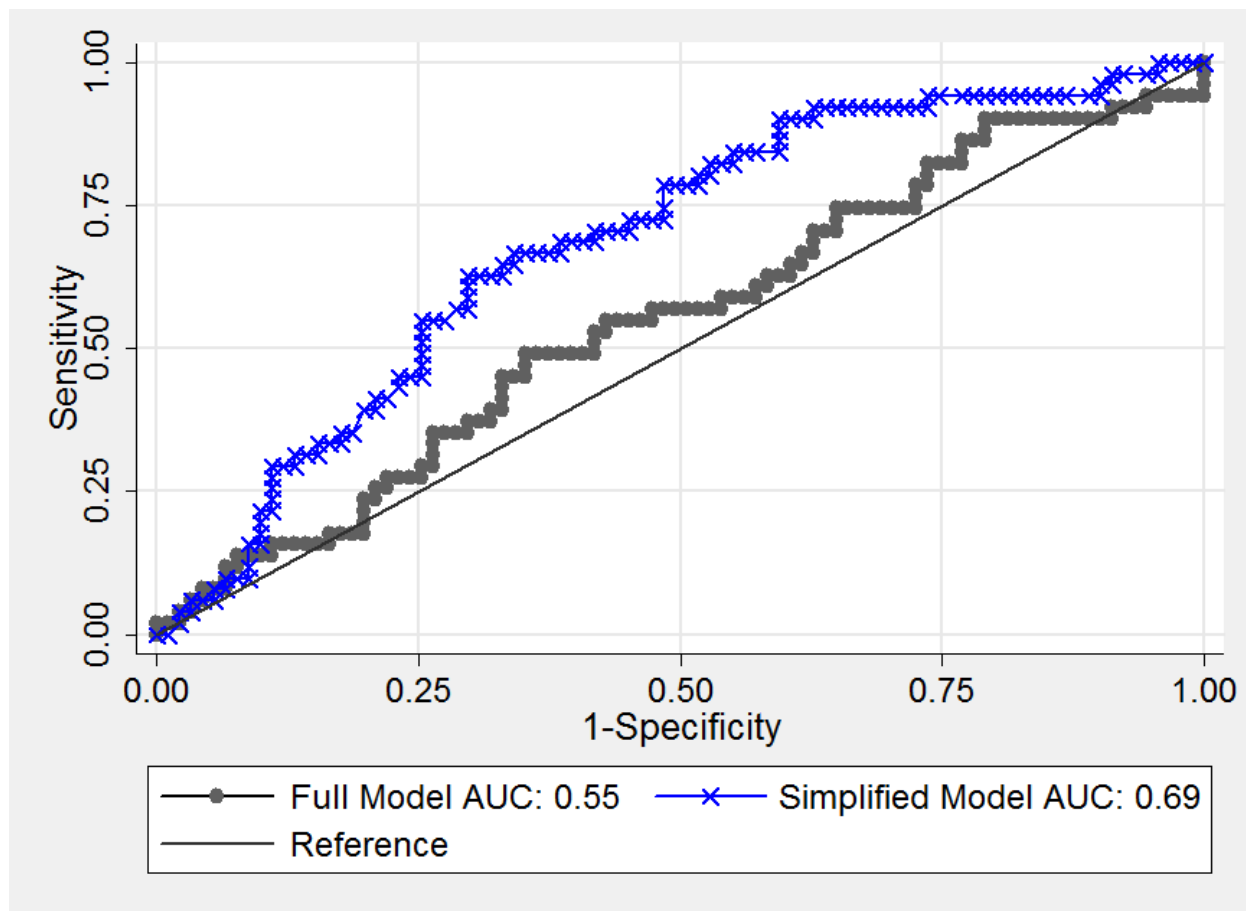


Figure 4.3. ROC Curves of the Full Model and the Simplified Model in Model Development

Using all data for model development, the final parameters of both the Full Model and the Simplified Model were estimated using logistic regression analyses. Based on the model parameters (Table 4.3), prediction algorithms were developed for both models and used in the following model testing stage.

Table 4.3. Main model results from logistic regression

	Model development (initial lapses) (n=142)			Model validation (second initial lapses) (n=95)		
	B(S.E.)	p	OR (95%CI)	B(S.E.)	p	OR (95%CI)
<u>Demographics</u>						
Age, M(SD)	-0.01(0.03)	0.78	0.99 (0.94, 1.05)			
Female, N(%) *	1.02(0.48)	0.03	2.78 (1.09, 7.06)	1.03(0.38)	0.006	2.79 (1.34, 5.84)
Race, N(%)						
Caucasian	0.22(1.07)	0.84	1.24 (0.15, 10.06)			
African American	0.23(1.19)	0.85	1.25 (0.12, 13.01)			
Hispanic	-0.17(1.65)	0.92	0.84 (0.03, 21.47)			
Education, M(SD)	0.28(0.19)	0.15	1.32 (0.9, 1.93)			
<u>Distal Risks</u>						
Dichotomized factors (yes/no), N(%)						
Drug use	0.3(0.5)	0.55	1.35 (0.51, 3.56)			
Unemployed	-0.84(0.64)	0.19	0.43 (0.12, 1.52)			
Mental health issue	-0.35(0.48)	0.47	0.71 (0.28, 1.8)			
Trauma history	0.42(0.48)	0.38	1.52 (0.59, 3.88)			
Has supporter	-0.07(1.29)	0.96	0.93 (0.07, 11.74)			
Risk taker	-0.23(0.47)	0.62	0.79 (0.32, 1.99)			
Will live alone	0.14(0.69)	0.84	1.15 (0.3, 4.41)			
Will live in shelter	-0.77(0.56)	0.17	0.46 (0.15, 1.39)			
Continuous factors, M(SD)						
Drinking quit attempts	0(0.01)	0.79	1 (0.99, 1.01)			
Treatment history	0.07(0.04)	0.12	1.07 (0.98, 1.17)			
Age starts drinking	0(0.05)	0.94	1 (0.9, 1.11)			
Age when drinking becomes problems	0.02(0.03)	0.47	1.02 (0.96, 1.09)			
Sobriety chance	0.01(0.01)	0.38	1.01 (0.99, 1.04)			
<u>Proximal Risks</u>						
Recovery progress	-0.05(0.02)	0.01	0.95 (0.92, 0.99)	-0.05(0.02)	0.003	0.95(0.92, 0.98)
Latent use profiles						
High users	-0.6(0.72)	0.41	0.55 (0.13, 2.26)			
Medium users	0.28(0.45)	0.54	1.32 (0.54, 3.2)			
Constant	-2.71(2.47)	0.27	0.07	-0.41(0.31)	0.183	0.67
Nagelkerke R ²	0.234			0.161		

4.4.2 Model Testing

The probabilities of the second initial lapses (that is the initial lapse in the second lapse episode) were estimated using the logistic regression algorithms developed in the model development stage. Compared to the Full Model (AUC=0.753, 95%CI[0.628,0.877], the Simplified Model showed worse predictability with lower ($p=0.045$) area under the ROC curve (AUC=0.647, 95%CI[0.512,0.783]) (Fig. 4.4). Therefore, the Full Model may be more generalizable to the initial lapses in the later episodes than the Simplified Model.

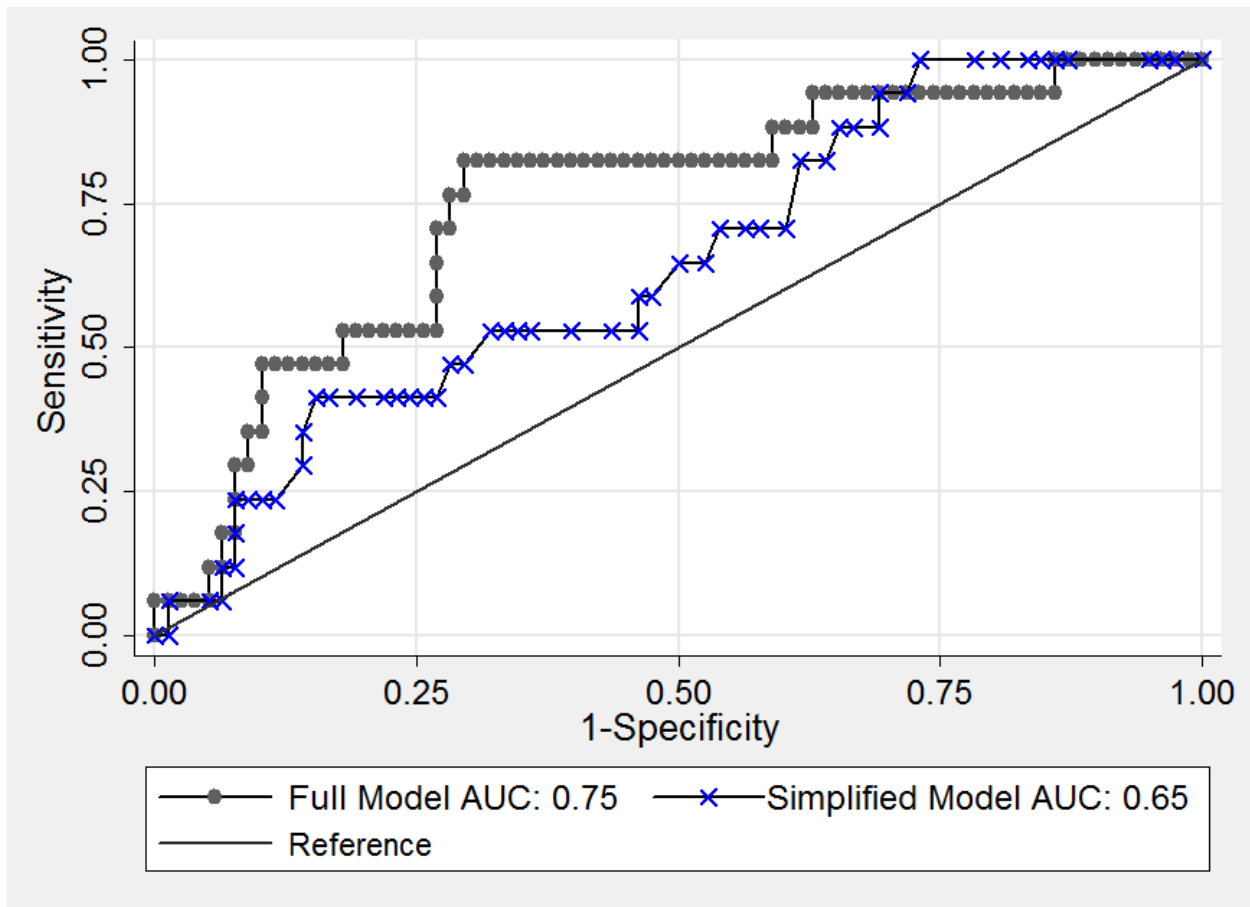


Figure 4.4. ROC Curves of the Full Model and the Simplified Model based on Model Testing Results

4.4.3 Sensitivity analyses

Three other alternative models were developed and compared to the Full Model and the Simplified Model as sensitivity analyses (Table 4.4). All predictors in the Full Model were included in the Model 1 but the latent use patterns were replaced with the nine individual use measures (such as AM Entry, CC Exposure, and RE Over-time engagement...etc.). Model 2 had the overall recovery progress as the only predictor. Model 3 had these nine individual use measures as the predictors. To avoid the potential multi-collinearity in Model 1 and Model 3, these three individual use measures (i.e., the total entry, total exposure, and total engagement) that were originally included in the latent class model in the previous work (Chih, 2013b) were not included in these models. In the results of the 10-fold cross-validation, the Model 1 and 3 had low AUCs as the Full Model. Although Model 2 has a higher AUC (that shows better predictability) than the Full Model, however, the difference ($p=0.255$) is not statistically significant after adjusting for multiple comparisons. In the model testing stage using the second initial lapse cases, the predictability (based on AUC) of Model1 increased to 0.73; this improved prediction is similar to that of the Full Model. Model 2 and 3 retained its similar predictability in the model testing stage, as compared to the same models in the model development stage.

Table 4.4. Sensitivity analyses results

		Model development— 10-fold cross-validation (n=142)		Model testing (n=95)	
	Predictors	AUC ¹ (95%CI)	P ² (compared to the AUC of Full model)	AUC (95%CI)	P (compared to the AUC of Main model)
Full Model	Demographic, distal, proximal factors	0.548 (0.449,0.647)	N.A.	0.753 (0.625, 0.880)	N.A.
Simplified Model	Gender, Recovery Progress	0.686 (0.597,0.775)	0.007	0.647 (0.512,0.783)	0.167
Model1	Full model but with all use measures	0.560 (0.462, 0.659)	0.992	0.730 (0.607, 0.853)	0.984
Model2	Only recovery progress	0.646 (0.550, 0.743)	0.255	0.647 (0.507, 0.787)	0.412
Model3	Only all use measures	0.559 (0.461, 0.656)	0.999	0.532 (0.382, 0.681)	0.140

Note: 1. AUCs in the Model Development were the pooled AUCs from the 10-fold cross-validation analyses. 2. p-values in this table were adjusted for multiple comparisons using the Sidak's method.

4.5 Discussion

The mHealth has drawn great attention recently due to its potential to innovate the addiction recovery programs. This study was to develop a predictive model of the initial lapses among patients who were diagnosed with alcohol use disorder and given A-CHESS, a mHealth intervention, just before they left the residential care. The purpose is to study whether a comprehensive list of predictors, particularly the continuous data collected in A-CHESS (i.e. the self-reported recovery status and the A-CHESS use data), may help to predict the users' initial lapse behavior in the upcoming week so that the just-in-time and personalized intervention via A-CHESS can be realized. The proposed Full Model considered a wide range of predictors, including demographics, distal risk factors, and proximal risk factors (from the Weekly Check-in data and A-CHESS use data). Using the variable selection method, the Simplified Model that

contained only two predictors (i.e. gender and recovery progress) was derived from the Full Model. The 10-fold cross validation analyses showed that the Simplified Model (AUC=0.686) actually had better predictability than the Full Model (AUC=0.548) with a p-value at 0.002. Therefore, the Simplified Model may be more suitable to predict the initial lapses of the new patient users. In the model testing stage using the initial lapse cases from the second lapse episodes, the predictability of the Full Model was improved (AUC=0.753) and became better than ($p=0.045$) that of the Simplified Model (AUC=0.647). Hence, the Full Model may be more suitable to predict the initial lapses in the later episodes once the model was developed using the initial lapse cases in the first lapse episode.

The models developed in this study have the potential to enhance the current lapse prediction service provided in A-CHESS (Chih et al., 2014). The mode behind the current A-CHESS prediction service was based on the recovery progress score and the recent lapse history. In this prior model, those who lapsed recently are more likely to lapse again (Chih et al., 2014). Hence, this model could be improved in terms of its predictability for those who did not lapse recently (that is to the initial lapse). The resulting two models from this study showed good predictability of the initial lapses and therefore may be applied to improve the current lapse prediction algorithm in A-CHESS.

The sensitivity analyses help to further understand the current results. In the sensitivity analyses, the subjective, self-reported recovery progress has shown to have stable and acceptable predictability of the initial lapses (around 0.65 of AUC, see Model2). Based on the results of Model3, the individual, objective A-CHESS use measures showed no predictability of the initial lapses, no matter in the initial or later lapse episodes. Generally, the results showed that simple

models (the Simplified Model and Model2) have better predictability for the initial lapse cases while more complex models (the Full Model and Model1) have better predictability for the initial lapse cases in the second lapse cases. One plausible reason of this finding could simply be that the initial alcohol lapse was hard to predict. Most demographics, distal risk factors, and A-CHESS use patterns (at least in the initial stage of use) may not be good predictors of the initial lapse. However, once the model incorporated the initial lapse cases, the model can predict the second initial lapse cases well. Using the early cases to build a model that was then used to predict later cases of the same individual patients is not ideal because the early and later cases of the same individuals may not be totally independent. This limitation was acknowledged and addressed in a later paragraph.

An observation in this study about A-CHESS use behavior was interesting. The results in Table 4.2 showed that the average A-CHESS use before the initial lapse cases was higher than that before the second initial lapse cases which happened later in time. This decreasing A-CHESS use patterns also follows the law of attribution which says that the use of health information interventions generally decreases over time (Eysenbach, 2005). Therefore, an interesting question is what happened to those who sustained their A-CHESS use over time. Were they better or worse off than those who stop using A-CHESS? In Table 4.2, A-CHESS use between the lapsers and non-lapsers was mostly compatible among the initial lapse cases. However, among the second initial lapse cases, the lapsers' A-CHESS use was generally lower than the non-lapsers. Therefore, when A-CHESS use decreases over time, those who still maintain a certain level of A-CHESS use may not lapse. In another A-CHESS publication, Gustafson et al. (2014) reported that "more" A-CHESS use may be related to the improved alcohol recovery

outcome in a randomized controlled trial (Gustafson et al., 2014). Adding to the same line of findings, the present study further explains that the sustained and longer A-CHESS use pattern may be the contributing factor of the better alcohol use outcome.

The mHealth technology presents an incredible opportunity for researchers and developers to transform addiction treatment (McClernon & Roy Choudhury, 2013). This study is the realization of multiple evaluation methods, which has been called by researchers in the field of mHealth research (Kumar et al., 2013). This study is one in a series of papers that aim to develop a theory-based and methodology-sound predictive model that can be implemented as a lapse prediction and support service in A-CHESS. When the possibility of lapse prediction appeared during a recent efficacy trial testing A-CHESS, several challenges were presented. Each of these challenges were addressed in a systematic way through psychometric evaluation of the instrument (Chih, 2013a), latent profile analysis of the underlying A-CHESS use patterns (Chih, 2013b), and two different predictive modeling techniques—Bayesian network model (Chih et al., 2014) and logistic regression model at the present study. This study and the other papers in this series may offer a complete example for the future studies in evaluating mHealth technology.

Several limitations exist in this study. First, the data used in this analysis were based on patients' Weekly Check-in. If patients did not fill out Weekly Check-in as described in data preparation section 4.3.4 (e.g. two consecutive Weekly Check-in within 14 days), their data would not be included in the analyses. However, patients who did not fill out Weekly Check-in may have some valid and non-ignorable reasons that could be potentially related to their substance use status. For instance, some patients who drank might not want to disclose their drinking status in A-CHESS but would tell their counselors at a different setting. This non-random missingness

may limit the generalizability of the results. The predictive model found in this study may not be applied to all alcohol addiction patients but only those who would use A-CHESS and Weekly Check-in. Second, we have a limited sample size (only 142 for the initial lapse cases and 95 for second initial lapse cases). The limitation of the sample size may cause the loss of statistical power and less precise model parameter estimates. Moreover, because of the limited sample size, the two datasets were selected based on different Weekly Check-ins but from the same participants. Even, based on the current literature, the model testing data were selected as the beginning of a new lapse episode, and therefore could be seen as the second initial lapse cases. The potential effect from the previous lapse may not be totally ignorable. From the predictive modeling perspective, it is better to have enough participants that can be divided into two different samples, one for model development and one for testing or external validation. Further studies including data from more participants and from participants in other agencies or regions may improve the model predictability and generalizability. Third, the lapse status reported in the Weekly Check-in was self-reported and totally voluntary. As mentioned earlier, it is likely that some patients may be reticent to report a lapse. Even so, the self-reported lapses may still assist in predicting and preventing the chance of the initial lapse among those who do accurately report. Future studies that collect objective, clinical-based measures, assessments from close families and friends, and/or the sensor information, like GPS and accelerometer, may help to improve or validate the current results. Last, researchers have used more frequent data collection methods in addiction behavior research (Shiffman et al., 2007). The data used in this study were collected weekly, not as frequent as other methods, like ecological momentary assessment (EMA) (Serre et al., 2012). More frequent data collection may offer more precision but may also

cause response fatigue, which is not feasible for long term use. To balance this tradeoff may require further research on the optimal data collection frequency or innovative methods that adjust the frequency based on the changing needs of patients.

A-CHESS is an example of applying mHealth in addiction treatment. This study and the others have shown the great potential of such an approach (Chih et al., 2014; Gustafson, Shaw, et al., 2011; McTavish et al., 2012). The predictive modeling is one way to unlock the power of the data that are currently available in mHealth interventions. To offer personalized and continuous support to patients with addiction via mHealth will improve patient outcomes but require further research to develop and refine the interventions and the theories behind.

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