User Modeling for Pervasive Alcohol Intervention Systems

Ugan Yasavur
School of Computing and Information Sciences
Florida International University
Miami, FL
uyasa001@fiu.edu

Reza Amini
School of Computing and Information Sciences
Florida International University
Miami, FL
ramin001@fiu.edu

Christine Lisetti
School of Computing and Information Sciences
Florida International University
Miami, FL
lisetti@cs.fiu.edu

ABSTRACT

In this paper, we have proposed a user model for computer based drinking behavior change intervention and recommender systems. We discuss specific requirements of user modeling in health promotion and specifically alcohol interventions. We believe that making behavior change systems available pervasively may lead to better and sustainable results. Therefore, our proposed user model takes advantage of the target-behavior related features such as contextual features (e.g., social interactions, location, and time). The proposed user model uses well-validated questionnaires to capture target-behavior specific aspects. We also introduced approaches for enhancing users' experience in the model creation stage by using Embodied Conversational Agents(ECAs) and users' affective states.

Keywords

User modeling, tailoring, alcohol intervention, behavior change, lifestyle change recommender systems (LSCRS).

1. INTRODUCTION

The positive effect of tailoring and personalization on lifestyle change systems is evidenced by several studies [20] [33] [34]. For effective tailoring in lifestyle change systems, comprehensive user characteristics and personal profile/model related to the target behavior need to be acquired and maintained.

Explicit and implicit modeling is needed in healthy behavior promotion systems. In addition, the user model for health behavior change systems must be specialized according to a target behavior (e.g excessive drinking, lack of exercise, obesity). Explicit ways to create a user model or user profile may include conducting assessments with the use of validated questionnaires, psychometric instruments and screening instruments. Implicit ways to build user-profile may include tracking motivation, stage of change, affective features, spatio-temporal events and some data interpretation and mining.

Paper presented at the Workshop on Recommendation Technologies for Lifestyle Change 2012, in conjunction with the 6th ACM conference on Recommender Systems.

Lifestyle@RecSys'12, September 13, 2012, Dublin, Ireland.

Explicit modeling is generally used in the initial user profile creation stage and does not require continuous updates. Implicit modeling facilitates the maintenance of context-related variables in order to increase the context-awareness (e.g. users' physical and social environments) of the system.

After initial creation of a user profile, context-related and affective features need to be kept up-to-date and other profile features must be updated less frequently.

We focus on one target behavior, namely alcohol consumption related behavior change. Therefore, our proposed user model targets lifestyle change systems which aim to promote decreasing or stopping alcohol consumption.

In the following sections, first we study the state of the art in user modeling in life style change recommender systems and behavior change intervention systems in Section 2. Then, we extend the explicit(target-behavior specific) and implicit(target-behavior related) features to build and maintain a user model in Section 3.

2. RELATED RESEARCH

Personalization and tailoring are used in variety of different domains including e-commerce[24], social networks [35], entertainment [18] [7] and health [26] [27]. Whereas collaborative and content-based recommender systems provide a good level of personalization in e-commerce, social networks and entertainment domains, the behavior change domain requires a different approach. The demographic information, user interests, goals, background information and individual traits are the most commonly used user profile features in recommender systems. While these features are still useful in health behavior change systems, different target behaviors requires different modeling features (e.g. consequences of drinking and dependence on alcohol for drinking behavior change; and family history and Body Mass Index (BMI) for obesity).

In addition to personal information, it is useful to benefit from research on context-aware systems [2]. By the increase in usage of smart mobile phones and mobile social network applications, it has recently become possible to track context-related information about users. The most widely used features in context-aware systems are location [7] and time [18] [7]. It is also useful for health promotion recommender systems to use findings of context-aware systems which focus on inferring users' states and activities including social interactions [36] [32]. From continuously posted data on social networks, it is possible to detect social interaction [6].

Recently, there has been an increasing interest in user modeling based on affective features [4]. The user's affective states can be an indicator for the relevance of the recommended item to the user's interest.

In behavior change systems, personalization according to affective state plays a particularly important role because delivering appropriate messages according to current emotions of the user can increase the effectiveness of health promotion interventions [25].

In the health intervention systems which use Embodied Conversational Agents(ECAs)[13] as a user interface, additional personalization can increase the efficacy of the intervention system. Several studies show that concordance of patient and physician increases patient satisfaction [15] [23]. Also, related research on race concordance of the virtual character and the user implies that racial adaption of ECA and user has positive impact on user's satisfaction [25].

In the context of the computer-based alcohol interventions, although there exists some effort in web-based alcohol interventions for personalization and tailoring, they mainly focus on personalization of feedback for conducted assessments [9] [27], [19].

While all mentioned interventions provide personalized feedback, few of them [27], [19] provide feedback based on theoretical constructs (e.g., Transtheoretical Model of Behavior Change). Drinker's Check Up (DCU) [19] provides personalized feedback based on available normative data and uses elements of behavior change models. Responsible Drinking Program[27] makes further personalization by dynamically tailoring feedback across multiple interactions of the client. Although the explicit information acquired from the users is only used for tailoring the feedback, these brief interventions provide good sources for target-behavior specific user modeling. They do not focus on user modeling and personalization in the course of long term behavior change period.

It has been concluded by several extensive surveys on alcohol interventions [8] [43] that computer based interventions have positive effect on reducing or stopping drinking. To maintain motivation and make the behavior change sustainable, we can use behavior change support systems in the form of social networks, mobile applications, lifestyle change recommender systems, and motivational systems.

In the next section we discuss our proposed comprehensive user model which can be used as a reference for alcohol intervention systems and behavior change support systems.

3. THE PROPOSED USER MODEL

Our proposed user model is shown in Figure 1. The model is updated after each assessment and after perception of new affective and contextual features of the user. Assessments provide information about different aspects of the client's drinking. We use some well-validated [19] assessment instruments to gain understanding of the user's drinking psychometric aspects. In addition to assessment results, it is beneficial to monitor the user's affective states via a camera to be able to adapt the recommendations and messages with the user's affective states.

The proposed user model is composed of features grouped under two categories, *target-behavior specific features* (explicit features) and *target-behavior related features* (implicit features). In the following sections, we explain the importance of each feature and the aspects of the problematic drinking behavior that each feature captures.

3.1 Target-Behavior Specific Features

Our target behavior in this paper is *alcohol drinking*. So, in this section we focus on the assessment instruments which can capture specifically the user's alcohol consumption behavior features. The assessments used in this paper are standardized assessment measures proved to be effective in alcohol consumption behavior change [40].

3.1.1 Consequences of Drinking

"Drinking Consequences" feature set assesses the *negative consequences* of the user's drinking. Drinker's Inventory of Consequences (DrInC) [28] is a reliable, valid, clinically useful, and self-administered instrument to assess the negative consequences of drinking. DrInC includes a set of questions in *five different* areas: physical, inter-personal, intra-personal, impulse control, and social responsibility.

The user answers each question in a 4-point Likert scale. Then, by adding up the responses in each area, we calculate his/her score in that area. These scores show the severity of an individual's problems.

The recommender system can use these scores in order to prepare the best personalized feedbacks and recommendations based on the consequences that alcohol has had on the user's life. According to the [28] this feature set should be updated on weeks 1, 8, 16, 26, 52, and 68 of intervention.

Intra-Personal: This feature is assessed using 8 questions which reflect the *subjective perceptions* of the user about her/his drinking. These questions query the user's feeling experienced because of drinking (bad, unhappy, or guilty), personality change experiences (e.g. aggressive, depressive), interference with personal growth, moral life, interests and activities, and interested lifestyle.

Inter-Personal: The focus of this feature is to find out the impact of drinking on the *user's relationships*. So, we query the user's experiences of damage/loss of friendship/love, impairment of parenting and causing harm to the family, concern about drinking from family or friends, damage to reputation, and embarrassing actions while drinking. The assessment of this feature is performed using 10 questions.

Social Responsibility: We use this feature to describe the role-fulfillment of the user from the *other people's point of view*. We use 7 questions to query the user's work/school problems (missing days, poor quality, fired or suspended), financial problems, and failings to meet expectations.

Physical: This feature is assessed using 8 questions that reflect the *negative physical states* resulting from user's drinking. These questions query the user's hangovers, sleeping problems, sickness, harm to health, appearance, eating habits, sexuality, and injury while drinking.

Impulse Control: This feature includes 12 questions about other *unhealthy lifestyles* exacerbated by drinking (e.g., smoking, drugs, and overeating), risk taking and impulsive actions of the user, troubles with law, and damages to people and property.

3.1.2 Motivation to Change

To assess the stage of user's *readiness* and *motivation to change*, we use an instrument called SOCRATES [31]. This instrument involves 19 questions categorized in three domains: *ambivalence*, *recognition*, and *taking steps*. Questions are answered in a 5-point Likert scale. A behavior change recommender system can use these scores to capture the readiness of the user to change before providing recom-

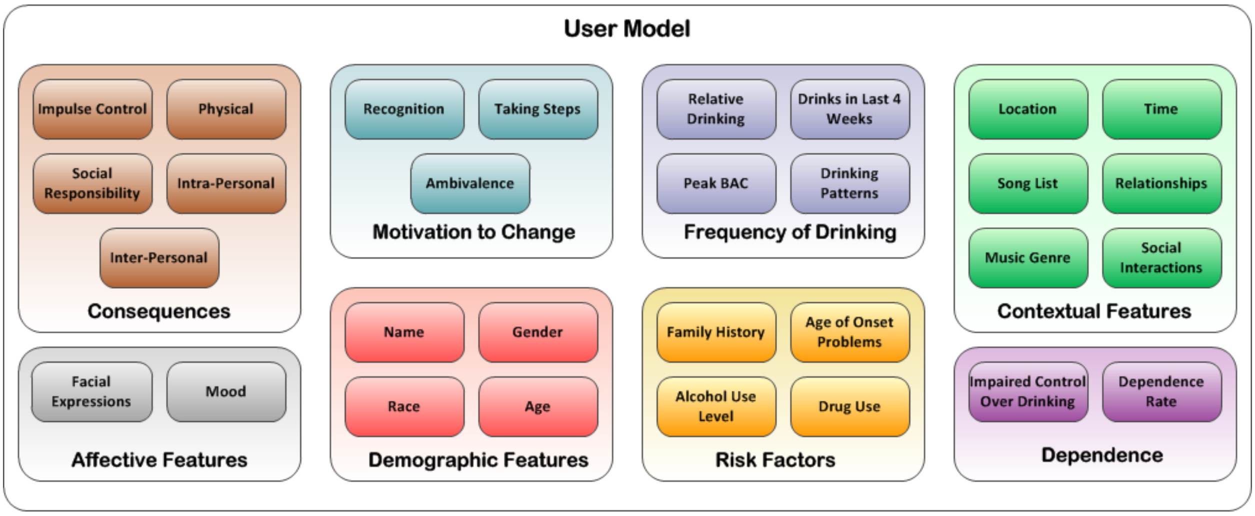

Figure 1: User Model

mendations to change the user's behavior change.

Recognition: The recognition score shows the degree of the user's *awareness* about his/her drinking problems, and the degree of his/her *desire* to change. Therefore, higher degrees of this feature show more desire and motivation to change from the user.

Ambivalence: Ambivalence score shows the degree of *uncertainty* of the user about whether s/he drinks too much, is in control, is hurting others, or is alcoholic. A high ambivalence score shows openness of the user to change. A low ambivalence score has two possible reasons: (1) user knows that his drinking is causing problems (high Recognition); or (2) user knows that s/he does not have drinking problems (low Recognition).

Therefore, we can use this feature to decide whether the user is open to reflections and recommendations or is not ready yet.

Taking Steps: This feature shows the degree of the user's *successful experience in changing* drinking behavior. So, high "Taking Steps" score can be interpreted as (1) need help to persist on the change behavior, and (2) need help to prevent backsliding to the previous drinking behaviors. On the other hand, low scores in this feature show no recent behavior changes in user.

3.1.3 Dependence to Alcohol

We assess the user's degree of dependence to the alcohol using a self-administered 20-item questionnaire called Severity of Alcohol Dependence Questionnaire (SADQ-C) [41]. This feature can be used to predict the likelihood of achieving control-drinking goals, and likelihood of withdrawal.

Questions are answered in a 4-point Likert scale, so the range of the score will be from 0 to 60. Scores higher than 30 for males and 25 for females show severe alcohol dependence and probable need of medical intervention. Scores in 16-30 range show moderate dependence. Otherwise, the user has mild physical dependency.

3.1.4 Risk Factors

We use the Brief Drinker Profile (BDP) [30] to assess some information about the family drinking history, other drug use, additional life problems, motivation for treatment, and history of problem development. Information derived from this feature set can be used in selecting the treatment approaches for user [29] in the behavior change recommender systems. According to the BDP manual [30], the non-static features of this group should be updated every three months.

Age of Onset Problems: This feature involves the user's age in which s/he first took a drink, the age in which s/he first became drunk, and the age in which drinking started affecting his/her life. This feature is static and does not need updates later.

Family History: This feature includes the alcohol problem history of the person's family. User can place his/her family drinking in different categories of abstainer, light drinker, moderate drinker, heavy drinker, problem drinker, or alcoholic. If the user's family does not have any drinking history, it means that his/her drinking patterns were acquired, not inherited. To assess genetic risk factors, the alcohol problems of his/her other biological relatives are queried too.

Drug Use: Since using other drugs can increase the risk of alcohol problems, the type and frequency of the possible used drugs in the last 3 months is queried.

AUDIT Score: Alcohol Use Disorders Identification Test (AUDIT) [5] is a 10-item questionnaire that we use to identify people whose alcohol consumption has become hazardous or harmful to their health. The amount and frequency of drinking, alcohol dependence, and problems caused by alcohol are queried using this instrument. Questions are scored using a 5-point Likert scale. The total score is the summation of all the answers. Table 1 shows the way AUDIT scores are interpreted.

The cut-off numbers may be different based on average body weight, gender, race, and cultural standards.

3.1.5 Frequency of Drinking

This category of features describes the user's drinking patterns and amount of alcohol consumption. So, the alcohol behavior change recommender systems can use them as indicators of the user's drinking pattern and provide more personalized recommendations for the user.

Table 1: AUDIT score interpretation.

AUDIT Score	Interpretation
score < 4	No drinking problems
4 ≤ score ≤ 8	Harmful for ages under 18 and females
score > 8	Alcohol dependence
8 < score ≤ 15	Should be advised to reduce drinking
16 ≤ score ≤ 19	Should be suggested counseling
score ≥ 20	Should be warranted further diagnose

Drinking Pattern: A drinker may have one of the two drinking patterns: *steady* or *periodic*. A drinker with steady drinking pattern drinks at least once a week and about the same amount every week. A drinker with periodic drinking pattern drinks less often than once a week and is abstinent between drinking episodes.

Drinks in Last 4 Weeks: This feature includes the number of standard drinks that a user had per week in the last four weeks. A standard drink is a 12 oz beer (5% alcohol), a 5 oz wine (12.5% alcohol), or a 1.5 oz liquor (40% alcohol).

Relative Drinking: This feature shows the user's statistical standing relative to the other U.S. people with the same gender.

Peak BAC: Blood Alcohol Concentration (BAC) is the amount of alcohol contained in a person's blood and is measured as weight per unit of volume. Widmark's [44] basic formula for calculating BAC is as follows:

$$\%BAC = (A \times \frac{5.14}{W} \times r) - 0.015 \times H \qquad (1)$$

Where, "A" is the total number of liquid ounces of alcohol that the person has drunk since the commencement of drinking. It is calculated by multiplying the number of liquid ounces of drink by its percentage of alcohol. "W" is the person's weight in pounds. "r" is the alcohol distribution ratio which is 0.73 for men and 0.66 or women. "H" is the number of hours between commencement of drinking and the time of BAC calculation.

3.2 Target-Behavior Related Features

These features are not specific to the target behavior but they are implicitly related with the target behavior. For example, demographic information of the user have significant role in personalizing the recommendations and using the normative data to interpret the *target-behavior specific features*. As a concrete example, the normative data used for rating the dependence to alcohol and consequences of drinking depend on the user's gender, race, and age. In addition to the demographic information, we studied affective and contextual features which provide important target-behavior related information.

3.2.1 Demographic Features

Demographic features can be used to improve interpretation of the other feature scores and to improve interaction with the user. Studies [28], [22] show that people of different **genders**, **ages**, and **ethnicities** experience different types of negative consequences after drinking. For example, women have more sleeping problems after drinking while men have more sexual and money problems after drinking.

Therefore, taking the demographic data into account in the user model enables recommending more accurate feedback and exercises to the user.

We can build rapport with the user by calling the user with his/her **name** during the intervention and personalize his/her experience.

For the systems that use ECAs as the interface, they can adapt the ECA's **race** and **gender** to the user's. Research shows that patient-physician race concordance can lead to better health outcomes [15] and that people respond to the ethnicity of ECAs in the same ways of that of humans.

3.2.2 Affective Features

The problem drinkers, who experience intense feeling of depression, discontent and indifference to the world around them, report that they drink to relax or reduce anxiety symptoms [39]. Another research found that emotions and affective states of a person, depending on personality types, predict motives for problem drinking [16]. Therefore emotions and affective states of a problem drinker is crucial for the user model. They can help to fine-tune appropriateness of recommendations and interventions and improve context awareness.

The emotions and affective states can be also used to improve user's experience in the systems which use ECAs as the user interface. The user's experience may affect implicitly the amount and accuracy of the disclosed information. Building a close relationship with the user facilitates his/her behavior change and affects the accuracy of the information disclosed [38], [42].

While the instruments demonstrated can be used as self-administered via form-based interface, the suggested style to administer them is to be delivered via a face-to-face interview [28]. The face to face interviews can be conducted by ECAs [25] which can build a close relationship with the user and have positive effects on the interview process.

Monitoring the facial expressions and mood helps to determine the user's emotions and affective states. In the next section, we described each of these non-verbal signals in more details.

Facial Expressions: According to [3], the facial expressions are the most important modalities in human behavioral judgment. Thus, including facial expressions in human affect analysis can increase the accuracy [12] of the analysis.

Using facial expressions, the behavior change recommender system can recognize the effect of the recommended message/feedback on the user, and his/her affective state.

The user's emotional facial expressions can be recognized through a camera using a real-time facial expression recognition system and categorized into the universal emotion categories [17]: happy, sad, angry, surprised, and neutral.

Mood: Mood is the user's background state of well-being which is often modeled on a bipolar scale of positive-negative valence. Mood changes much slower than emotion and lasts longer time (e.g, minutes to days). Therefore, unlike facial expressions that are updated in real-time, mood can be updated less frequently (e.g., every 5 minutes) in the user model.

To capture the user's mood, we suggest to get the average of the user's categorized emotional facial expressions in a time window and to classify the user's emotions to positive and negative emotions.

3.2.3 Contextual Features

The advancement of the technology on mobile devices, increasing usage of mobile applications, and location-based social networking systems such as Facebook Location[1] and FourSquare[2] introduced new possibilities in development of the context-aware systems. Other than location and time information, social networking and micro-blogging services (Twitter[3]) also offer possibilities to track mood [11], social interactions, relationships, and social ties of the user.

Recently, increased popularity of the music-based social networks[4] and their tight integration to the general purpose social networks introduced new possibilities to improve context awareness of the systems. Research [14] shows that listening some music genres is positively associated with alcohol use. It is also possible to identify personal song lists which lead to alcohol use by tracking multiple context related parameters. For example variation of mood depending on the listened songs and music genres might give important insight about the factors which prepare appropriate psychological conditions for alcohol use.

The location, time of the day, social interactions and mood tracking [11] can help to understand specific conditions which result in alcohol use such as physical environment, psychological conditions, and social conditions.

Several studies show the relationship between reasons and motivations for drinking [1], [22], [21]. Their results imply that contextual awareness will have positive effect on intervention and support systems.

These results implies that personalization and tailoring, based on the contextual factors, are crucial for the alcohol intervention and behavior support recommender systems. Thus, in our proposed user model, we propose to use available information from social networking services and mobile applications to monitor drinking related contextual features.

4. CONCLUSION

In this paper we proposed a user model for alcohol related lifestyle change recommender systems. We proposed target-behavior specific features and target-behavior related features for the user model. We identified the importance of each feature group for the alcohol related intervention and recommender systems. We proposed a user model composing of *eight different groups of features*, *consequences of drinking*, *motivation to change*, *dependence to alcohol*, *risk factors*, *frequency of drinking*, *demographic* features, *affective* features, and *contextual features*.

5. REFERENCES

[1] A. Abbey, M. J. Smith, and R. O. Scott. The relationship between reasons for drinking alcohol and alcohol consumption: An interactional approach. *Addictive Behaviors*, 18(6):659 – 670, 1993.

[2] G. Adomavicius and A. Tuzhilin. *Recommender Systems Handbook*. Springer US, Boston, MA, 2011.

[3] N. Ambady and R. Rosenthal. Thin slices of expressive behavior as predictors of interpersonal consequences: A meta-analysis. *Psychological Bulletin*, 111(2):256–274, 1992.

[4] I. Arapakis, I. Konstas, and J. M. Jose. Using facial expressions and peripheral physiological signals as implicit indicators of topical relevance. In *Proceedings of the 17th ACM international conference on Multimedia*, MM '09, pages 461–470, New York, NY, USA, 2009. ACM.

[5] T. F. Babor, J. C. Higgins-Biddle, J. B. Saunders, and M. G. Monteiro. *AUDIT: The Alcohol Use Disorders Identification Test. Guidelines for use in primary health care.* World Health Organization, Department of Mental Health and Substance Dependence, 2 edition, 2001.

[6] N. Banerjee, S. Agarwal, V. Bahl, R. Chandra, A. Wolman, and M. D. Corner. Virtual Compass: relative positioning to sense mobile social interactions. In *Proc. Eighth International Conference on Pervasive Computing*, number LNCS 6030, pages 1–21, Helsinki, Finland, May 2010.

[7] V. Bellotti, B. Price, P. Rasmussen, M. Roberts, D. J. Schiano, A. Walendowski, B. Begole, E. H. Chi, N. Ducheneaut, J. Fang, E. Isaacs, T. King, M. W. Newman, and K. Partridge. Activity-based serendipitous recommendations with the Magitti mobile leisure guide. *Proceeding of the twenty-sixth annual CHI conference on Human factors in computing systems - CHI '08*, page 1157, 2008.

[8] B. M. Bewick, K. Trusler, M. Barkham, A. J. Hill, J. Cahill, and B. Mulhern. The effectiveness of web-based interventions designed to decrease alcohol consumption–a systematic review. *Preventive medicine*, 47(1):17–26, July 2008.

[9] B. M. Bewick, K. Trusler, B. Mulhern, M. Barkham, and A. J. Hill. The feasibility and effectiveness of a web-based personalised feedback and social norms alcohol intervention in UK university students: a randomised control trial. *Addictive behaviors*, 33(9):1192–8, Sept. 2008.

[10] T. Bickmore. Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human*, 12(2):293–327, 2005.

[11] J. Bollen, H. Mao, and X. Zeng. Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8, Mar. 2011.

[12] G. Caridakis, L. Malatesta, L. Kessous, N. Amir, A. Raouzaiou, and K. Karpouzis. Modeling naturalistic affective states via facial and vocal expressions recognition. In *Proceedings of the 8th international conference on Multimodal interfaces*, pages 146–154. ACM, 2006.

[13] J. Cassell and E. J. Sullivan, S. Prevost, & E. Churchill. Embodied Conversational Agents. *Social Psychology*, 40(1):26–36, 2000.

[14] M.-J. Chen, B. a. Miller, J. W. Grube, and E. D. Waiters. Music, substance use, and aggression. *Journal of studies on alcohol*, 67(3):373–81, May 2006.

[15] L. a. Cooper, D. L. Roter, R. L. Johnson, D. E. Ford, D. M. Steinwachs, and N. R. Powe. Patient-centered communication, ratings of care, and concordance of patient and physician race. *Annals of internal medicine*, 139(11):907–15, Dec. 2003.

[16] M. L. Cooper, V. B. Agocha, and M. S. Sheldon. A motivational perspective on risky behaviors: the role of personality and affect regulatory processes. *Journal of personality*, 68(6):1059–88, Dec. 2000.

[1] http://www.facebook.com/about/location
[2] https://foursquare.com
[3] http://www.twitter.com
[4] http://www.spotify.com

[17] P. Ekman, W. V. Friesen, and P. Ellsworth. What emotion categories or dimensions can observers judge from facial behavior? In P. Ekman, editor, *Emotion in the human face*, pages 39–55. Cambridge University Press, New York, 1982.

[18] D. Gavalas and M. Kenteris. A web-based pervasive recommendation system for mobile tourist guides. *Personal and Ubiquitous Computing*, 15(7):759–770, May 2011.

[19] R. K. Hester, D. D. Squires, and H. D. Delaney. The Drinker's Check-up: 12-month outcomes of a controlled clinical trial of a stand-alone software program for problem drinkers. *Journal of substance abuse treatment*, 28(2):159–69, Mar. 2005.

[20] P. Krebs, J. O. Prochaska, and J. S. Rossi. A meta-analysis of computer-tailored interventions for health behavior change. *Preventive medicine*, 51(3-4):214–21, 2010.

[21] E. Kuntsche, R. Knibbe, G. Gmel, and R. Engels. Who drinks and why? A review of socio-demographic, personality, and contextual issues behind the drinking motives in young people. *Addictive behaviors*, 31(10):1844–57, Oct. 2006.

[22] J. W. LaBrie, J. F. Hummer, and E. R. Pedersen. Reasons for drinking in the college student context: the differential role and risk of the social motivator. *Journal of studies on alcohol and drugs*, 68(3):393–8, May 2007.

[23] T. a. Laveist and A. Nuru-Jeter. Is doctor-patient race concordance associated with greater satisfaction with care? *Journal of health and social behavior*, 43(3):296–306, Sept. 2002.

[24] G. Linden and B. Smith. Amazon. com recommendations: Item-to-item collaborative filtering. *Internet Computing, IEEE*, 7(February):76–80, 2003.

[25] C. Lisetti, U. Yasavur, C. D. Leon, and R. Amini. Building an On-Demand Avatar-Based Health Intervention for Behavior Change. *Proceedings of the Twenty-Fifth International Florida Artificial Intelligence Research Society Conference*, 2012.

[26] M. L. a. Lustria, J. Cortese, S. M. Noar, and R. L. Glueckauf. Computer-tailored health interventions delivered over the Web: review and analysis of key components. *Patient education and counseling*, 74(2):156–73, Feb. 2009.

[27] L. Mauriello. An Internet-Based Computer-Tailored Intervention to Promote Responsible Drinking: Findings from a Pilot Test with Employed Adults. *Alcoholism Treatment*, 30(1):1–15, 2011.

[28] W. Miller and J. Tonigan. *The drinker inventory of consequences (DrInC)*. 1995.

[29] W. R. Miller and R. K. Hester. Matching problem drinkers with optimal treatments. In W. R. Miller and N. Heather, editors, *Treating addictive behaviors Processes of change*, pages 175–203. Plenum Press, 1986.

[30] W. R. Miller and G. A. Marlatt. Brief Drinker Profile. *Psychological Assessment Resources, Odessa, FL*, 1984.

[31] W. R. Miller and J. S. Tonigan. Assessing drinkers' motivation for change: The Stages of Change Readiness and Treatment Eagerness Scale (SOCRATES). *Psychology of Addictive Behaviors*, 10(2):81–89, 1996.

[32] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell. Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application. In *Proceedings of the 6th ACM conference on Embedded network sensor systems*, SenSys '08, pages 337–350, New York, NY, USA, 2008. ACM.

[33] S. Noar, C. Benac, and M. Harris. Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions. *Psychological bulletin*, 133(4):673, 2007.

[34] S. M. Noar, N. Grant Harrington, S. K. Van Stee, and R. Shemanski Aldrich. Tailored Health Communication to Change Lifestyle Behaviors. *American Journal of Lifestyle Medicine*, 5(2):112–122, Nov. 2010.

[35] D. Quercia and J. Ellis. Using mobile phones to nurture social networks. *IEEE Pervasive Computing*, 09:12–20, 2010.

[36] K. K. Rachuri, M. Musolesi, C. Mascolo, P. J. Rentfrow, C. Longworth, and A. Aucinas. Emotionsense: a mobile phones based adaptive platform for experimental social psychology research. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*, Ubicomp '10, pages 281–290, New York, NY, USA, 2010. ACM.

[37] C. R. Rogers. The necessary and sufficient conditions of therapeutic personality change. *Journal of Consulting Psychology*, 21(2):95–103, 1957.

[38] B. G. Silverman, J. Holmes, S. Kimmel, C. Branas, D. Ivins, R. Weaver, and Y. Chen. Modeling emotion and behavior in animated personas to facilitate human behavior change: the case of the HEART-SENSE game. *Health care management science*, 4(3):213–28, Sept. 2001.

[39] M. M. Spada and A. Wells. Metacognitions, emotion and alcohol use. *Clinical Psychology & Psychotherapy*, 12(2):150–155, Mar. 2005.

[40] D. D. Squires and R. K. Hester. Using technical innovations in clinical practice: the Drinker's Check-Up software program. *Journal of clinical psychology*, 60(2):159–69, Feb. 2004.

[41] T. Stockwell, D. Murphy, and R. Hodgson. The severity of alcohol dependence questionnaire: its use, reliability and validity. *British journal of addiction*, 78(2):145–155, 1983.

[42] a. L. Suchman, K. Markakis, H. B. Beckman, and R. Frankel. A model of empathic communication in the medical interview. *JAMA : the journal of the American Medical Association*, 277(8):678–82, Feb. 1997.

[43] A. White, D. Kavanagh, H. Stallman, B. Klein, F. Kay-Lambkin, J. Proudfoot, J. Drennan, J. Connor, A. Baker, E. Hines, and R. Young. Online alcohol interventions: A systematic review. *J Med Internet Res*, 12(5):e62, Dec 2010.

[44] E. M. P. Widmark. *Principles and Applications of Medicolegal Alcohol Determination*. Biomedical Publications, Davis, California, 1981.