# I Can Help You Change! An Empathic Virtual Agent Delivers Behavior Change Health Interventions

CHRISTINE LISETTI, REZA AMINI, UGAN YASAVUR, and NAPHTALI RISHE,
Florida International University

We discuss our approach to developing a novel modality for the computer-delivery of Brief Motivational Interventions (BMIs) for behavior change in the form of a personalized On-Demand VIrtual Counselor (ODVIC), accessed over the internet. ODVIC is a multimodal Embodied Conversational Agent (ECA) that empathically delivers an evidence-based behavior change intervention by adapting, in real-time, its verbal and nonverbal communication messages to those of the user's during their interaction. We currently focus our work on excessive alcohol consumption as a target behavior, and our approach is adaptable to other target behaviors (e.g., overeating, lack of exercise, narcotic drug use, non-adherence to treatment). We based our current approach on a successful existing patient-centered brief motivational intervention for behavior change—the Drinker's Check-Up (DCU)—whose computer-delivery with a text-only interface has been found effective in reducing alcohol consumption in problem drinkers. We discuss the results of users' evaluation of the computer-based DCU intervention delivered with a text-only interface compared to the same intervention delivered with two different ECAs (a neutral one and one with some empathic abilities). Users rate the three systems in terms of acceptance, perceived enjoyment, and intention to use the system, among other dimensions. We conclude with a discussion of how our positive results encourage our long-term goals of *on-demand conversations*, anytime, anywhere, with virtual agents as personal health and well-being helpers.

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Author's address: C. Lisetti; email: lisetti@cis.fiu.edu.

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## 1. INTRODUCTION

There is a growing societal need to address the increasing prevalence of *behavioral health issues*, such as obesity, alcohol or drug use, and general lack of treatment adherence for a variety of health problems. The statistics—worldwide and in the U.S.—are daunting. Excessive alcohol use is the third leading preventable cause of death in the United States [National Center for Chronic Prevention and Health Promotion 2011] (with 79,000 death annually) and is responsible for a wide range of health and social problems (e.g., risky sexual behavior, domestic violence, loss of job). Alcoholism is estimated to affect 10–20% of U.S. males and 5–10% of females sometime in their lifetimes. Similar risks exist with other forms of substance abuse. In 2010, the World Health Organization (WHO) reported that obesity worldwide has more than doubled since 1980. In 2011, 1.5 billion adults in the world were overweight, of which 500 million were obese, and 43 million children under the age of five were overweight [WHO 2011]. In the U.S. alone, obesity affects 33.8% of adults, 17% (or 12.5 million) of children and teens, and has tripled in one generation. These behavioral issues place people at risk of serious diseases, for example, obesity can lead to diabetes, alcoholism to cirrhosis, physical inactivity to heart disease.

On the positive side though, these behavioral health issues (and associated possible diseases) can often be prevented with relatively simple lifestyle changes, such as loosing weight with a diet and/or physical exercise or learning how to reduce alcohol consumption. Medicine has therefore started to move towards finding ways of preventively promoting wellness rather than solely treating already established illness. In order to address this new focus on well-being, health promotion interventions aimed at helping people change lifestyle have been designed and deployed successfully in the past few years.

Evidence-based patient-centered *brief motivational interviewing (BMI) interventions* have been found particularly effective in helping people find intrinsic motivation to change problem behavior (e.g., excessive drinking, overeating) after short counseling sessions, and to maintain healthy lifestyles over the long term [Dunn et al. 2001; Emmons and Rollnick 2001]. A methodological review of clinical trials of 361 treatments showed that out of 87 treatment methods, the top two ranked treatment styles were (1) brief interventions and (2) motivational enhancement therapies [Miller and Rollnick 2002]. It is reported that five minutes of advice and discussion about behavioral problems (e.g., alcohol or drug use) following a screening can be as effective as more extended counseling and that a single session can be as effective as multiple sessions [Babor and Grant 1992].

Lack of locally available personnel well-trained in BMI, however, often limits access to successful interventions for people in need. Yet, the current epidemic nature of these problems calls for drastic measures to rapidly increase access to effective behavior change interventions for diverse populations. To fill this accessibility gap, evidence has accumulated about the general efficacy of *computer-based interventions (CBIs)* [Bewick et al. 2008; Cunningham et al. 1999; Hester and Delaney 1997; Portnoy et al. 2008; Skinner 1994].

The success of CBIs, however, critically relies on insuring engagement and retention of CBI users so that they remain motivated to use these systems and come back to use them over the long term, as necessary (e.g., for booster sessions, follow-ups, lifestyle maintenance sessions). Whereas current BMI interventions delivered by computers have been found effective, high drop-out rates due to their users' low level of engagement during the interaction limit their long-term adoption and potential impact [Portnoy et al. 2008; Vernon 2010].

One crucial aspect positively affecting the health outcomes of BMIs (and most counseling techniques, for that matter) involves the ability of the therapist to establish rapport and to express empathy [Miller and Rollnick 2002]. *Empathy* is a complex phenomenon with no established definition to date. However, there is a general consensus that empathy can involve cognitive attributes or affective attributes which can also be combined during full-blown empathy [Goldstein and Michaels 1985]. *Cognitive attributes* of empathy involve cognitive reasoning used to understand another person's experience and to communicate that understanding [Hojat 2007] (or putting oneself in someone else's shoes). *Emotional* or *affective attributes* of empathy, on the other hand, involve physiological arousal and spontaneous affective expressive responses to someone else's display of emotions [Wispé 1987] (e.g., people often unconsciously mimic someone else's perceived expressions of distress or joy). Someone can have a reflex-like affective physiological reaction to someone's experience (without cognitively understanding it), or a cognitive understanding of that person's situation (without physically expressing it), or both.

Because of their text-based-only interfaces, current CBIs can therefore only express limited empathy (mostly reflected in the choice of textual wording of the intervention).

Fortunately in the last decade, at the same time as CBIs are being developed and studied in healthcare, information systems research has promoted the study of emerging technologies for healthcare systems [Davis et al. 2010]; and computer science research has progressed in the design of simulated human characters and avatars with anthropomorphic communicative abilities [Cassell et al. 2000] as emerging technologies that can change the fundamental nature of human-computer interactions. Expressive virtual characters have become increasingly common elements of user interfaces for a wide range of applications, such as interactive learning environments, e-Commerce, digital entertainment, and virtual worlds.

Virtual characters who specifically focus on dialog-based interactions are called *embodied conversational agents (ECAs)*, also known as *intelligent virtual agents (IVAs)*. ECAs are digital systems created with an anthropomorphic embodiment (be it graphical or robotic) and capable of having a conversation (albeit, still limited) with a human counterpart using some artificial intelligence broadly referred to as an "agent". With their anthropomorphic features and capabilities, they interact using humans' innate communication modalities, such as facial expressions, body language, speech, and natural language understanding, and can also contribute to bridging the digital divide for low-reading and low-health literacy populations, as well as for technophobic individuals [Bickmore et al. 2009; Neuhauser and Kreps 2011].

In this article, we posit that (1) using well-designed virtual empathic characters or ECAs for the delivery of BMIs has the potential to increase users' engagement and users' motivation to continue to interact with them, and that as a result, (2) users' increased exposure to engaging evidence-based BMIs will increase their effectiveness for behavior change.

In the rest of this article, we first review current research on motivational brief interventions (BMI) and embodied conversational agents (ECA). We then discuss our approach to develop a novel modality for the computer-delivery of brief motivational interventions (BMIs) for behavior change in the form of a 3D personalized *On-Demand VIrtual Counselor (ODVIC)*, accessed anytime anywhere over the internet and shown in Figure 1. We currently focus our work on alcohol consumption as a target behavior based on a successful evidence-based BMI intervention, the Drinker's Check-Up (DCU) [Miller et al. 1988], whose existing computer-based delivery via a text-based interface has been shown to significantly help problem drinkers reduce alcohol consumption [Hester et al. 2005].

We then discuss how we designed our ODVIC to partially simulate both aspects of empathic communication (affective and cognitive), using a scheme for the agent's dynamic display of facial expressions based on the user's perceived expressions (affective

Fig. 1. ODVIC Amy in her office.

empathy), and a scheme for verbal reflective listening with sentences that paraphrase and summarize the user's answers (cognitive empathy). Without claiming that our virtual character can fully empathize with the user, which would require the ability to subjectively experience and understand the user's feelings, we then show, with results of user studies evaluations, that our ODVIC has enough expressive abilities to provide the user with a better experience than when interacting with the DCU delivered with a text-only interface or with a non-expressive character.

We conclude with a discussion of how these results encourage our long-term goals for our on-demand conversations with virtual helping agents, who not only can help people find intrinsic motivation to change problem behavior but, even more importantly, who could also keep users engaged for long-term evolving exchanges about health-promoting lifestyles.

## 2. RELATED RESEARCH

### 2.1. Motivational Interviewing and Brief Motivational Interviewing Interventions

*Motivational interviewing (MI)* has been defined by Miller and Rollnick [2002] as a directive, client-centered counseling style for eliciting behavior change by helping clients to explore and resolve ambivalence. One of MIs central goals is to magnify discrepancies that exist between someone's goals and current behavior. MI basic tenets are that (a) if there is no discrepancy, there is no motivation; (b) one way to develop discrepancy is to become ambivalent; (c) as discrepancy increases, ambivalence first intensifies; if discrepancy continues to grow, ambivalence can be resolved toward change.

In the past few years, adaptations of motivational interviewing have mushroomed with the purpose of meeting the need for motivational interventions within medical and healthcare settings [Burke et al. 2002], where sessions can be as short as 20–40 minutes. Furthermore, whereas initially used with addictive behavior problems, such interventions have been adapted and implemented with great success for a variety of behaviors ranging from diabetes self-management [Doherty et al. 2000] to treatment adherence among psychiatric patients [Swanson et al. 1999] to fruit and vegetable intake among African Americans [Resnicow et al. 2000], among other target behaviors, which increases their appeal.

*Brief motivational interviewing interventions (BMIs)* combine MI style of communication with the common underlying elements of effective brief interventions characterized by the acronym FRAMES [Bien et al. 1993; Miller and Sanchez 1994]: *F*eedback about client's individual status is personalized; *R*esponsibility for changing is left with the individual; *A*dvice is provided in a supportive manner; *M*enus of different options for changing that respect individual's readiness to change are offered; *E*mpathic style of communication is central to the individual-clinician relationship; and *S*elf-efficacy is nurtured and emphasized.

Because BMIs are highly structured—first, *assessment* of target behavior patterns, then normative *feedback*, then *menu* of change options depending on the client's readiness—they lend themselves well to computer-delivery [Lisetti and Wagner 2008], while remaining effective [Bewick et al. 2008; Hester and Delaney 1997] and well-accepted by people [Cunningham et al. 1999; Skinner 1994].

*Internet-delivered interventions* in particular present a number of advantages over traditional modes of delivery [Portnoy et al. 2008]: they are able to reach a large audience in a cost-effective manner (possibly in remote locations) with 24-hour access; they offer participants privacy and anonymity (and users do divulge more about risky behaviors to them than to human counselors, e.g., getting drunk every night) [Servan-Schreiber 1986]); they can automatically tailor information derived from individual assessment to an individual's specific needs [Brug et al. 1996; Noar et al. 2007]; they can diminish variability between different counselors, which accounts for 25% to 100% changes in rates of improvement among clients [Miller and Rollnick 2002]; and they demonstrate infinite patience in respecting the individual's (sometimes very slow-coming) readiness to change [Prochaska and Velicer 1997]. It is also interesting to note that internet-delivered interventions for alcohol reduction are particularly useful for people less likely to access traditional alcohol-related services, such as women and young people [White et al. 2010].

One brief motivational interviewing intervention called the *Drinker's Check-Up (DCU)* [Miller et al. 1988] is the focus of our current work. DCU has been computerized as a menu-based text-only intervention delivered over the Internet that specifically targets excessive drinking behaviors and with which heavy drinkers can reduce their drinking by an average of 50% at a 12-month follow-up [Hester et al. 2005; Squires and Hester 2004].

Our On-Demand VIrtual Counselor ODVIC delivers the same intervention content as Hester's DCU, with additional empathic messages that we describe later.

### 2.2. Embodied Conversational Agents (ECAs)

One of the most influential works for the study of virtual animated characters established that, when provided with social cues by a computer system, humans react socially similarly to how they would with a human [Reeves and Nass 1996]. Because latest ECAs can use their sophisticated multimodal communication abilities to establish rapport [Gratch et al. 2006, 2007a; Huang et al. 2011; Kang et al. 2008a, 2008b; McQuiggan et al. 2008; Pelachaud 2009; Prendinger and Ishizuka 2005; von der Pütten et al. 2009; Wang and Gratch 2009, 2010], communicate empathically [Aylett et al. 2007; Boukricha and Becker-Asano 2007; Boukricha and Wachsmuth 2011; Boukricha et al. 2009; McQuiggan and Lester 2007; Ochs et al. 2012; Prendinger and Ishizuka 2005] and engage in social talk [Bickmore and Giorgino 2006; Bickmore and Picard 2005; Bickmore et al. 2005; Cassell and Bickmore 2003; Kluwer 2011; Schulman et al. 2011], they have become capable of being as engaging as humans and have even been found more engaging than humans at times [Gratch et al. 2007b].

Several avatar-based health intervention or counseling applications have been developed for a variety of contexts [Bickmore and Picard 2005; Bickmore et al. 2009; Johnson and LaBore 2004; Silverman et al. 2001], and their evaluation indicates that users tend to accept them as interesting counterparts that improve their interaction with health interventions, with many users expressing the wish for characters to be less predictable and more expressive.

After we first identified MI-based interventions as particularly useful for health dialog systems [Lisetti 2008; Lisetti and Wagner 2008], some researchers have continued to explore the use of 2D cartoon or comic-like characters to provide MI-related material to patients or to train healthcare personnel in MI [Magerko et al. 2011; Schulman et al. 2011]. Although the avatars employed in these mentioned systems have shown some promising acceptance by their users, because they are 2D, they lack dynamic expressiveness, which is key for communicating facial affect [Ehrlich et al. 2000], itself essential in establishing the MI requirement of an empathic communicative style [Miller and Rollnick 2002].

Our current work is an effort to address these issues. We use 3D characters who are able to sense the user's facial expressions, display facial expressions dynamically in real time, and adapt to these in real time according to a model of nonverbal empathic communication designed for brief motivational interventions.

## 3. HEALTH COUNSELOR SYSTEM ARCHITECTURE

In an effort to address the limitations of current computer-based interventions, namely, users' loss of interest over the long term and dropouts (which are also problematic in classical face-to-face interventions), our approach is to leverage users' acceptance of ECAs documented early on as increasing enjoyment and engagement with computer systems [Cassell et al. 2000] by developing an expressive empathic 3D animated character with Text-to-Speech and lip synchronization using the 3D Haptek engine. Our virtual agent is able to perceive the user's (or client's) facial expressions and text entries as it delivers the adapted content of the DCU (the evidence-based patient-centered BMI previously described) [Hester et al. 2005; Squires and Hester 2004] in an empathetic style. It combines (1) partial nonverbal mimicry (head nods and facial expressions), also known as parallel empathy and important in building rapport [Bavelas et al. 1986], and (2) verbal reflective listening (RL) considered one of the main ways of conveying empathy in patient-centered interventions [Rogers 1959].

### 3.1. System Overview

Our system architecture is composed of the main modules shown in Figure 2. The modules are the same as the ones described in detail Lisetti [2012], except for the Empathy Module which has been substantially improved for this current study, as we describe later.

In short, during any interaction, the user's utterances are processed by the *Dialog Module* which directs the sessions and elicits information from the user; the user's facial expressions are captured in real time and processed by the *Empathy Module* in an attempt to assess the user's most probable affective states and convey an ongoing sense of empathy via a *Multimodal Interface* (using 3D animated virtual character with verbal and nonverbal communication abilities); *Psychometric Analysis* is performed based on the information collected by the Dialog Module, and its results are stored in the *User Model* to offer a dynamically *Tailored Intervention* in the form of sensitive tailored feedback or specific behavior change plans.

### 3.2. Dialog Module

The Dialog Module evaluates and generates dialog utterances using three key components: a *Dialog Planner*, an *MI-Based Dialog Engine* (capable of expressing verbal empathy via reflective listening), and a collection of *Psychometric Instruments* (e.g., questions about drinking behavior patterns, family history). The interaction of the client with the system is based on a series of dialog sessions, each having a specific

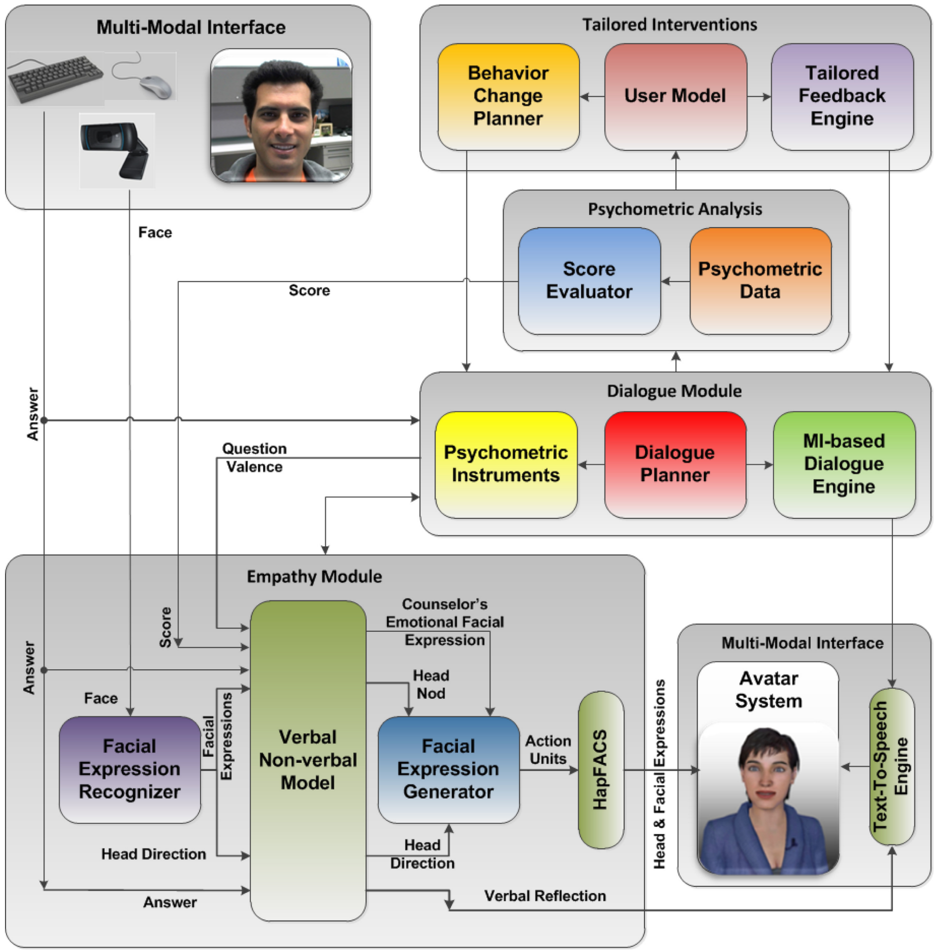


Fig. 2. ODVIC: On-demand VIrtual Counselor Architecture.

assessment goal to identify different aspects of the user's behavioral problem (if any), and in this article, we focus on excessive intake of alcohol. Each session is based on psychometric instruments which the *Dialog Planner* uses as a plan so that the dialog-based interaction can be conducted based on the knowledge that the system has acquired about the user, and on the user's current entries and affective states.

*Psychometric Instruments.* We use the collection of well-validated *Psychometric Instruments* commonly used by therapists to assess an individual's alcohol use [Miller and Rollnick 2002], and specifically those used in DCU [Hester et al. 2005]. Each psychometric instrument contains a set of questions which represent the plan for an assessment session. For example, one instrument (DrInC, 50 items) is used to identify consequences of the client's drinking problem with five different parameters (e.g., interpersonal relationships, work), and these are stored in the user model (see the following). These instruments include the Alcohol Use Disorders Identification Test (AUDIT), the Brief Drinker's Profile (BDP, 30-day alcohol use data), the Drinker's Inventory of Consequences (DrInC, 50 items), the Severity of Alcohol Dependence (SAD, 22 items), and the Stages of Change Readiness and Treatment Eagerness Scale

(SOCRATES, 19 items). After answering any of these self-reports, the user is offered immediate feedback about their drinking behavior, or they may continue and get overall feedback (described in the Feedback session).

*Dialog Planner*. The *Dialog Planner* component of the dialog module decides what type of utterance is to be generated based on the previous interaction in that session, that is, it decides the next stage of the session. For instance, when the system needs to assess the client's awareness of the consequences of his/her drinking, the Drinker Inventory of Consequences (DrInC) psychometric instrument is used as the plan for the session, and each question is assigned one of the five topics of the DrInC (e.g., interpersonal, intrapersonal). To measure consequences in each area, there are sets of non-sequentially positioned questions for each area, and these questions are conceptually related with each other.

The dialog planner aims at detecting discrepancies between the received answers for questions in the same area. If the dialog planner detects a discrepancy in the client's answers, then it calls the MI-Based Dialog Engine which generates an MI-style dialog in the form of reflective listening (explained next) to help the user become aware of the discrepancy (see earlier discussion on main tenets of MI for the importance of detecting discrepancies in MI). If no such discrepancy nor ambivalence is detected in the user's answers, then the dialog planner continues with the assessment session.

*MI-Based Dialog Engine*. The *MI-Based Dialog Engine* applies a finite set of well-documented MI techniques known under the acronym *(OARS): Open-ended questions*[1], *Affirmations, Reflective listening*, and *Summaries*, which are applied toward goals concerning specific behaviors (e.g., excessive alcohol use in this case, but as discussed earlier, could also be adapted to drug use, overeating). The MI-based dialog engine adapts each static psychometric instrument to interactive MI-style interaction and currently implements (1) Affirmations (e.g., "You have much to be proud off"; (2) Summaries ("Ok, so let me summarize what you've told me today about your experience during the last 90 days. You have had more than 20 drinks, during the last 90 days you have missed work about once every two weeks, you have frequently gotten into arguments with friends at parties, ..."; and (3) Reflections as in Reflective Listening (RL).

*Reflective listening* is a client-centered communication strategy involving two key steps: seeking to understand a speaker's thoughts or feelings, and then conveying the idea back to the speaker to confirm that the idea has been understood correctly [Rogers 1959]. Reflective listening also includes mirroring the mood of the speaker, reflecting the emotional state with words, and nonverbal communication (which we discuss next in the Empathy Module). Reflective listening is an important MI technique which the system simulates to help the client notice discrepancies between his or her stated beliefs and values and his or her current behavior.

There are many types of reflections, from *Simple Reflections*, to *Complex Reflections*, to *Double-Sided Reflections*. We currently implement *Simple Reflections* to cultivate awareness (e.g., Client: "I only have a couple of drinks a day." Counselor: "I see, so you have about 14 drinks per week."). We also use *Double-Sided Reflection* to summarize ambivalence, which can help to challenge patients to work through their ambivalence about change. Statements such as "So on the one hand, you like to drink and party, but on the other hand, you are then less likely to practice safe sex" can summarize and highlight a patient's ambivalence toward change [Botelho 2004]. Other double-sided reflections, such as "Ok, so your wife and children complain daily about your drinking, but you do not feel that your ability to be a good parent is at stake, is that right?", can

[1]We implemented the system handling Open-ended questions separately [Yasavur et al. 2013], and it is to be integrated with this intervention in future work.

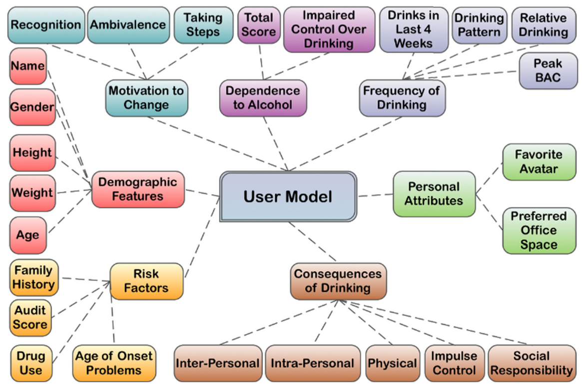


Fig. 3. User model.

magnify the discrepancies between the user's current parenting situation and what kind of parent he would like it to be.

### 3.3. Psychometric Analysis

As shown in Figure 2, *Psychometric Analysis* is concerned with processing *Psychometric Data* collected by the dialog module using the collection of psychometric instruments (described earlier) whose various questions drive the dialog module.

Based on instructions in each instrument, the *Score Evaluator* calculates the score of the user for a particular measuring instrument, according to normative data [NIAAA 1998]. The result is stored in the *User Model* (described next) in order to identify specific aspects of the drinking problem. For instance, the instrument assessing drinking patterns can locate the user on a spectrum of alcohol consumption (low, mild, medium, high, or very high), where a score above 8 indicates mild or higher problems. When provided feedback about this score (by the Tailored Feedback module discussed later), the user can make an informed decision about whether or not to continue with the offered self-help program. Respecting the MI spirit, the user is never persuaded or coerced, and can, at any moment, choose to exit the intervention, in which case the system gracefully terminates the conversation.

### 3.4. Tailored Interventions

*User Model*. The *User Model* (shown in Figure 3) enables the system to tailor its intervention to a specific user. Tailoring can be achieved in multiple ways: by using the user's name referred to as *personalization*, by using known characteristics of the user, such as gender, referred to as *adaptiveness* (e.g., women and men normative scores are calculated differently), and by using self-identified needs of the user, referred to as *feedback provision*.

Currently, the User Model collects the age, gender, weight, height, and first name or nickname to preserve anonymity.

In addition to static demographic information, the User Model includes different variables in six different areas: motivation, personal attributes, frequency of drinking, risk factors, consequences, and dependence. Each area consists of multiple variables to assess specific aspects of the problem from different view points. These psychometric data are calculated based on the chosen psychometric instruments (described previously).

Because the intervention is designed to assist the user to change unhealthy behavioral patterns, it can be used over multiple sessions as on-demand follow-up sessions.

As the user continues to interact with the system over time, the user model can keep track of the fluctuating user's progress toward change in terms of the user's current level of ambivalence, by identifying and weighing positive and negative things about drinking; the user's readiness to change, from pre-contemplation to maintenance (or setbacks in between) [Prochaska and Velicer 1997]; as well as the result of other specialized self-report questionnaires (e.g., the user's awareness of the consequences of drinking).

*Tailored Feedback Engine.* The *Tailored Feedback Engine* generates tailored feedback based on the user model. Several studies showed that tailored health communication and information can be much more effective than nontailored ones because it is considered more relevant to that specific individual's needs [Noar et al. 2007]. Pre-identified subdialog scripts used in DCU [Hester et al. 2005] are reproduced for the various topics of feedback, for example, self-reported drinking, perceived current and future consequences of drinking, pros and cons of current consumption patterns, personal goals and their relation to alcohol use, readiness to change drinking behavior.

As pointed out in Hester et al. [2005], because the feedback module reveals discrepancies between the user's desired state and present state, it is likely to raise resistance and defensiveness. The style in which the feedback is given, therefore, needs to be empathetic enough to avoid generating defensiveness. The user receives feedback about the assessed self-check information, which is put in perspective with respect to normative data (e.g., "It might be surprising to you that according to the current national norm, 10% of man your age drink as much as you do").

*Behavior Change Planner.* The *Behavior Change Planner* component helps to create personalized behavior change plans for clients who are ready to change and is only entered by users who have received feedback from the Tailored Feedback Engine. The first step of the behavior change planner is to assess the user's readiness to change along a continuum from "Not at all ready" to "Unsure" to "Really ready to change". Depending upon the level of readiness, different submodules are performed, from printing feedback summary, to a guided self-change exploration, to negotiating goals and developing a plan to change via menus options. As with the previous modules, various gracious opportunities to exit the system (early) are offered to the user.

### 3.5. Empathy Module

The *Empathy Module* (and its evaluation) is one of the main foci of this article and enables the virtual agent to communicate empathically with the user or client during the behavior change intervention.

Discussing issues about at-risk behaviors, such as heavy drinking, are highly emotional for people to talk about (e.g., shame, discouragement, anger, hopefulness, satisfaction, pride). Empathy and positive regard toward the client are therefore critical therapeutic conditions to creating an atmosphere of safety and acceptance where clients feel free to explore and change [Miller and Rose 2009]. As discussed earlier, in MI and BMI sessions, what is crucial is the ability of the therapist to establish rapport and to express accurate empathy by applying "a skillful reflective listening to clarify and amplify the [user's] own experiencing and meaning" [Miller and Rollnick 2002].

There are major differences between the current research and our previous work [Lisetti et al. 2012]: (1) the previous research only involved the implementation of the character-based counseling framework, which had a very simple implementation of the empathy module. Complete development of the empathy module was one of our future directions in that research; (2) in the previous research, we were planning to have a preliminary empathy module which included nonverbal mimicry of the client's emotional facial expressions using a one-to-one mapping between the client's recognized emotional facial expressions and the counselor's emotional facial expressions; in the current research, however, empathy is modeled both verbally and nonverbally using the two affective and cognitive modules using a decision tree; (3) the facial expressivity of the virtual character is improved using the newly implemented module namely HapFACS [Amini and Lisetti 2013] (see the following Facial Expression Generator); and (4) in the previous research, we only included preliminary evaluation without evaluation of the virtual counselor in terms of the user acceptance and perceived character features.

*3.5.1. Empathy Module Overview.* The Empathy Module (cf., Figure 2) emulates two kinds of empathy: *affective empathy* and *cognitive empathy*. Affective empathy refers to the ability to react emotionally when one perceives that another is experiencing, or about to experience, an emotion [Wispé 1987]. Cognitive empathy involves an understanding (rather than a feeling) of another's experiences and concerns, combined with the capacity to communicate that understanding [Hojat 2007]. Whereas our system does not understand the subjective experience of the user's emotions, it does perceive the user's emotions (with computer vision) and reacts emotionally (with 3D real-time animations) to convey affective empathy and a sense of rapport.

The Empathy Module captures and processes user's facial expressions in real time to assess the user's most probable affective states, then combines it with affect-related information elicited from utterances to decide the counselor's empathic responses. It is responsible for verbal reflection of user's answers, and for other feedbacks, such as facial expressions, and head nods.

The Empathy Module uses a set of inputs to decide the counselor's empathic behaviors.

(1) *Emotional Facial Expressions.* Facial photos are taken using the camera through the JPEG-Cam Flash/Javascript library and sent to the Face/Head Processing Module. The system recognizes the client's emotional facial expressions and categorizes them into five categories of happy, sad, angry, surprised, and neutral. The Face/Head Processing Module uses the facial expression recognition algorithm proposed in Taigman and Wolf [2011] and Wolf et al. [2010].
(2) *Head Movements.* The Face/Head Processing Module returns degrees of the three possible head movements: *head yaw* (up/down), *head pitch* (left/right), and *head roll* (left/right roll).
(3) *Smile.* The Face/Head Processing Engine returns the user's smiling status as one of its outputs (smile with an open mouth). The smile status is slightly different from the happy facial expression. The happiness is recognized from different movements of the face, such as eyes, cheeks, and lips, whereas smile is only based on the state of the lips.
(4) *Counselor's Question Valence.* The counselor can expect whether her question will be pleasant or unpleasant for the client. So, the counselor simulates the role-taking mode of empathy and puts herself in the client's shoes to guess her/his emotion in response to asking each question. After asking a question, the client appraises it based on her/his goals and situation, and reacts emotionally to it. For each Psychometric Instrument, the Empathy Module uses the OCC [Ortony et al. 1988] cognitive structure of emotion to predict the client's emotions. Based on OCC, one feels *joyful* if she/he is *pleased* about a *desirable* event, and one feels *distressed* if she/he is *displeased* about an *undesirable* event.
(5) *Client's Answer to the Counselor's Question.* For any counselor's question, the client provides an answer through a menu-based interface using mouse/keyboard. The client's answers show whether her/his alcohol consumption is at risk level or not.

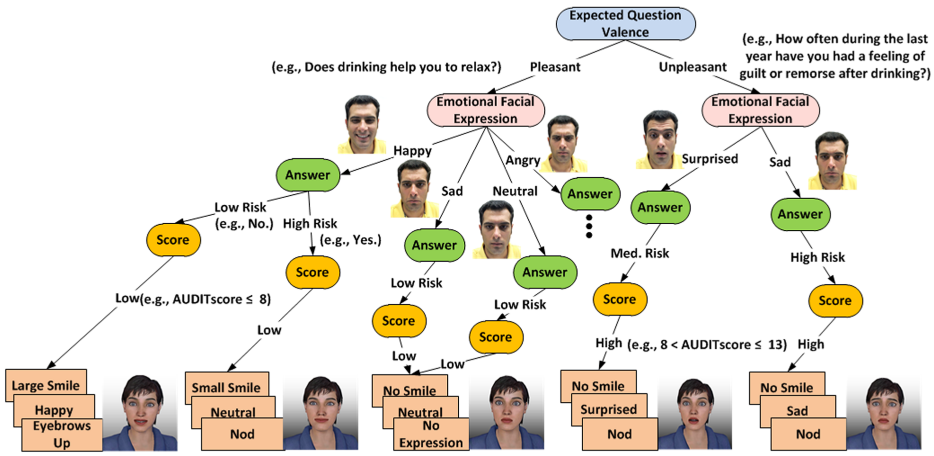


Fig. 4. A sample piece of the decision tree used in the cognitive module.

(6) *History of the Client's Previous Answers*. After receiving each answer from the client, the Score Evaluator Module of the Psychometric Analyzer calculates a score for the client based on her/his history of answers up to then. Based on the user model in different assessment sessions, this score can represent the strength of the client's dependence to alcohol, drinking risk factors, motivation to change, frequency of drinking, and consequences of drinking.

*3.5.2. Verbal and Nonverbal Communication Model.* The Empathy Module also consists of a *Verbal and Nonverbal Communication Model*. Given the preceding parameters, the empathy model decides which affective/cognitive empathic responses to express (e.g., reflective listening and nonverbal mimicry increases rapport [Lafrance 1979; Lafrance and Broadbent 1976]). The Empathy Module mirrors the client's facial movements by mapping them, at times, to the same facial movements of the counselor to create closeness with the client.

The Empathy Module contains a rule-based system which uses a set of predefined rules in a *Decision Tree* (shown in Figure 4) to decide the next counselor's empathic reaction to the client, both verbal and nonverbal. This system decides "what facial expression to express", "when to show head nods", "what eyebrow expressions to show", and "what complex verbal reflections to express."

It returns a *simple* verbal feedback to each client's answer from a pool of appropriate verbal feedbacks for that answer. As mentioned earlier, simple reflections can be a repetition or rephrasing of the client's response. For example, when the counselor asks "How often do you have a drink containing alcohol?", if the client selects the answer "Two to three times a week", then the counselor reflects back, "OK, you drink at least twice a week."

Similarly to simple reflections, after each answer, the counselor can respond with a more complex verbal reflections. For example, the counselor asks "Has a relative or friend, or a doctor or other health worker been concerned about your drinking or suggested you cut down?" If the client answers, "Yes, but not in the last year", then the counselor reflects back, "This shows they were concerned about you."

*3.5.3. Facial Expression Generator.* The *Facial Expression Generator* generates the virtual character's facial expressions and head movements based on the Facial Action Coding System (FACS) [Ekman and Freisen 1978], and Emotional FACS (EMFACS)

(a) AU1 (b) AU2-Left (c) AU22 (d) AU61

Fig. 5. Some expressions on 3D characters. (a) AU1; (b) AU2-Left; (c) AU22; (d) AU61.

[Friesen and Ekman 1983]. FACS is a system that taxonomizes human facial expressions, head, and eye movements. Movements of individual facial muscles are encoded by *action units (AUs)* which are the fundamental actions of individual muscles or groups of muscles, including eye movements (see Figure 5).

FACS is a common standard for systematically categorizing the physical expressions of the face and emotional facial expressions and has been found useful to psychologists and to virtual character animators. EMFACS is a method for using FACS to determine the facial actions that are relevant to expressing six specific emotions (alleged universal): happiness, sadness, fear, disgust, contempt, surprised, and anger.

*3.5.4. HapFACS.* The Facial Expression Generator uses *HapFACS*, an open source software that we created with Haptek software (`haptek.com`) to generate facial expressions based on FACS and EMFACS [Amini and Lisetti 2013]. Figure 5 shows various activated AUs, for example, Figure 5(d) shows AU61—corresponding to eye movements—activated to the left. See Amini and Lisetti [2013] for a full description of HapFACS, which we made freely available online to help others generate FACS-based psychologically validated facial expressions.

The Facial Expression Generator accepts the outputs of the Nonverbal/Verbal Model and maps them to their appropriate AUs. The AUs are then passed to the HapFACS API to generate the emotional facial expressions on the character's face.

We integrated other features considered necessary for health promotion interventions [Lisetti 2009], such as the selection of different avatars with different ethnicities in both genders to help simulating client-counselor race concordance (see Figure 5). We also applied basic human-computer interaction usability principles during the design of the interface.

## 4. EXPERIMENT AND EVALUATION OF THE EMPATHIC VIRTUAL CHARACTER

Since the performance criteria of the conversational agents such as virtual health counselors is dependent upon the satisfaction of their users, it is necessary to measure the users' perception of the agent's action.

We designed an evaluation scheme to evaluate the user's acceptance of the virtual counselor and evaluate the character's properties (e.g., likability, animacy, and anthropomorphism). We combined (see Section 4.1) two questionnaires developed by Heerink et al. [2009] and Bartneck et al. [2008] and adapted them to our health counseling application.

We hypothesize that counselors with different delivery modalities (i.e., virtual character vs. text) and different levels of empathizing abilities (e.g., with or without facial expressions displayed appropriately at specific times based on the content of the interaction) will have different effects on the quality of the interaction with users. We expect the character with empathic abilities (e.g., appropriate facial expressions, verbal reflective listening) to have more positive effects than a non-empathic character or text-only system in terms of the users' acceptance of the system, among other measures.

Whereas it may seem intuitive that the system with empathic abilities would outperform both the one without empathic displays and the text-only system, other studies found that non-empathic and textual systems can at times be perceived better than empathic ones with respect to some features [Bickmore and Picard 2005]. An earlier study where we only compared our two avatar systems—empathic vs. non-empathic—showed similar results (see [Amini et al. 2013] for details on different features than the ones presented in this article).

These findings motivated our choice to compare all three versions of our system: text-only, non-empathic character, and empathic character.

### 4.1. Procedure

We asked the participants to attend the first session of an interview with our virtual counselor, which includes the AUDIT [Babor et al. 2001] psychometric instrument to assess the client's dependence on alcohol and frequency of drinking. The clients sat in front of a computer with a camera connected to it. We gave them oral instructions about the way the system works. They had access to a computer mouse and keyboard to select their answers to the counselor's questions from multiple choice menus. Users had the option to choose their preferred counselor's gender and ethnicity among the available characters (Hispanic, Caucasian, African American), some of them are shown in Figure 5. The default counselor was a brunette Caucasian female (Amy) who speaks in English (shown in Figures 1, 2, 4, and 5(a)).

We have implemented three conditions for the experiment.

(1) *Text-Only Drinker's Check-Up (DCU)*. During the session, the exact same content of the DCU [Hester et al. 2005] is delivered to the user using text-only webpage frames.
(2) *Non-empathic Counselor*. Amy shows a neutral facial expression during the introduction and interview, does not empathize with the user, does not reflect on the user's answers, and ignores the user's changes of emotional state.
(3) *Empathic Counselor*. During the counseling session, Amy reacts to the client with verbal and nonverbal empathic reactions. She expresses different emotional facial expressions (happy, sad, concerned, surprised, and neutral); head gesture (nod); big/subtle smile; head posture mimicry (pitch, yaw, roll); eyebrow movement; and lip synchronized verbal reflections. Being polite and getting permission for pursuing the interview is an empathic technique, so at the beginning and end of the interview, Amy requests the user's permission to continue.
An interview session begins with a verbal introduction of the system by Amy. The introduction is followed by a permission request from the client by Amy to go to the next step. Then, she gives an overview of what will happen during the interview and asks for permission again to start the interview.
During the introduction, Amy shows a neutral face and does not provide any empathic responses to the participant. The interview session involves a set of questions about the user's drinking behaviors and a statistical feedback. For each question, the client selects an answer from a list of 3–5 answers. At the end of the interview, Amy asks for permission to give normative feedback about the user's drinking behavior in her/his age group and gender.
During the interview (excluding the introduction), Amy empathizes with the client using the Empathy Module (described in Section 3). After the feedback, the user is directed automatically to an online questionnaire (see Section 4.2) which debriefs her/him about the performance of the virtual counselor.

Participants were recruited from volunteer university students through fliers and emails. They were randomly assigned to each of the two counselor conditions, and the text-only third condition was performed later (although it is a limitation which we discuss in the Future Work section). From the total number of 81 users for all conditions, 26 were assigned to the empathic counselor, 25 to the non-empathic counselor, and 30 to the text-only version.

In the next section, we describe the after-experiment questionnaire used to debrief the clients about the acceptance and performance of the counselor.

### 4.2. Questionnaire

We designed an online after-experiment questionnaire to evaluate the counselor's empathy, anthropomorphism, animacy, likability, perceived intelligence, perceived safety, subjective performance, and user's acceptance. It is based on a combination of the Heerink et al. [2009] model and the "Godspeed questionnaire" [Bartneck et al. 2008].

Heerink's model evaluates the users' acceptance of assisting social artificial agents. Heerink designed 13 constructs, each represented by multiple statements. Users reply to these statements on a 5-point Likert scale ($-2$ to $+2$). For positive statements (e.g., "I enjoyed the health counselor talking to me"), $-2$ means "strongly disagree" and $+2$ means "strongly agree." For the negative statement (e.g., "I found the health counselor boring"), $-2$ means "strongly agree" and $+2$ means "strongly disagree."

We omitted three of Heerink's constructs: namely, Facilitating Conditions (FC) (or the objective factors in the environment that facilitate using the system), Perceived ADaptability (PAD) (or the perceived ability of the system to be adaptive to the changing needs of the user), and Use/UsagE (USE) (or the actual use of the system over a longer period in time). The construct definitions show that (1) FC evaluates the environment which is the same for both the empathic and non-empathic conditions in our experiment, (2) PAD and USE are not relevant for our study because our users only interact for a short time with our system. We use the remaining ten constructs with the following definitions.

— *Attitude (ATT)*. Positive or negative feelings about the technology. The statements used to evaluate the attitude of the clients toward the virtual counselor are (1) I think it's a good idea to use the counselor; and (2) the counselor would make my life more interesting.
— *Intention to Use (ITU)*. Outspoken intention to use the system over a longer period in time. We use the following statement to evaluate the clients' intention to use the system: (3) I think I'll use the system again.
— *Perceived Enjoyment (PENJ)*. Feelings of joy or pleasure associated by the user with the use of the system. The following statements are used in this category: (4) I enjoyed the counselor talking to me; (5) I enjoyed participating in this session with the counselor; (6) I found the counselor enjoyable; (7) I found the counselor fascinating; and (8) I found the counselor boring.
— *Perceived Ease of Use (PEOU)*. Degree to which the user believes using the system would be free of effort. We used five statements to evaluate the clients' perception about the system's ease of use: (9) I think I learned quickly how to use the health counselor; (10) I found the counselor easy to use; (11) I think I can use the counselor without any help; (12) I think I can use the counselor if there is someone around to help me; and (13) I think I can use the counselor if I have a good manual.
— *Perceived Sociability (PS)*. Perceived ability of the system to perform sociable behavior. The following statements are used in this category: (14) I consider the counselor a pleasant conversational partner; (15) I feel the counselor understands me; (16) I think the counselor is nice; and (17) I think the counselor is empathizing with me.

—*Perceived Usefulness (PU)*. Degree to which a person believes using the system would enhance his or her daily activities. The statements used for evaluating the perceived usefulness of the virtual counselor are (18) I think the counselor is useful to me; and (19) I think the counselor can help me.
—*Social Presence (SP)*. Experience of sensing a social entity when interacting with the system. The four statements used in this category are (20) When interacting with the counselor, I felt like I'm talking to a real person; (21) I sometimes felt as if the counselor was really looking at me; (22) I can imagine the counselor to be a living creature; and (23) Sometimes the counselor seems to have real feelings.
—*Trust (TRUST)*. Belief that the system performs with personal integrity and reliability. To evaluate the clients' trust toward the virtual counselor, we used the following statements: (24) I would trust the counselor if it gave me advice; (25) I would follow the advice the counselor gives me; (26) I feel better interacting with the virtual counselor than with a human counselor in terms of privacy; and (27) I disclose more information about my drinking to the virtual counselor than a human counselor.
—*Anxiety (ANX)*. Evoking anxious or emotional reactions when using the system. The statements used in this category are (28) I was afraid to make mistakes during the interview; (29) I was afraid to break something; (30) I found the counselor scary; and (31) I found the counselor intimidating.
—*Social Influence (SI)*. User's perception of how people who are important to him or her think about his or her using the system. We used the following statements for evaluating the social influence of the virtual counselor: (32) It would give a good impression if I should use the counselor later; and (33) I am comfortable to disclose information about my drinking to the counselor.

Bartneck et al. [2008] have defined another questionnaire model called "Godspeed" including five key concepts of Human-Computer interaction: anthropomorphism, animacy, likability, perceived intelligence, and perceived safety with the following definitions.

—*Anthropomorphism (ANT)*. Attribution of a human form, characteristics, or behavior to nonhuman concepts, such as robots, computers, and animals. In this category, we asked the clients to rate he following statements for evaluating the anthropomorphism of the virtual counselor: (34) I rate the counselor as Fake/Natural; (35) I rate the counselor as Machine-like/Human-like; (36) I rate the counselor as Unconscious/Conscious; (37) I rate the counselor as Artificial/Lifelike; and (38) I rate the counselor' moving as Rigidly/Elegantly.
—*Likability (LIKE)*. Degree to which the agent evokes empathic or sympathetic feelings of the user. To evaluate the likability of the counselor, clients rated the following statements: (39) I rate my impression as Dislike/Like; (40) I rate the counselor as Unfriendly/Friendly; (41) I rate the counselor as Unkind/Kind; (42) I rate the counselor as Unpleasant/Pleasant; and (43) I rate the counselor as Awful/Nice.
—*Animacy (ANIM)*. Degree to which a computer agent is lifelike and can involve users emotionally. The animacy of the virtual counselor is evaluated by rating the following statements: (44) I rate the counselor as Dead/Alive; (45) I rate the counselor as Stagnant/Lively; (46) I rate the counselor as Mechanical/Organic; (47) I rate the counselor as Inert/Interactive; and (48) I rate the counselor as Apathetic/Responsive.
—*Perceived Intelligence (PI)*. User's perception of how the agent is intelligent. The statements rated in this category are (49) I rate the counselor as Incompetent/Competent; (50) I rate the counselor as Ignorant/Knowledgeable; (51) I rate the counselor as Irresponsible/Responsible; (52) I rate the counselor as Unintelligent/Intelligent; and (53) I rate the counselor as Foolish/Moving Sensible.

—*Perceived Safety (PSA)*. User's perception of the level of danger and her/his level of comfort during the use. We evaluated the perceived safety of the virtual counselor using these statements: (54) During the interaction I was Anxious/Relaxed; (55) During the interaction I was Agitated/Calm; and (56) During the interaction I was Quiescent/Surprised.

## 5. RESULTS AND DISCUSSION

### 5.1. Results of the User's Experience

These 56 questions categorized in 15 classes are asked of the users. The clients' answers are analyzed using the Mantel-Haenszel-Chi-Square statistical method (degree of freedom $df = 1$) which involves (1) assigning scores to the response levels, (2) forming means, and (3) examining location shifts of the means across the levels of the responses.

We followed two null hypotheses: (1) text-only and avatar-based counselors have the same effects on the users; and (2) counselors with different levels of empathizing abilities (empathic vs. non-empathic) have the same effects on the users. A common significance threshold (i.e., alpha) value in the chi-square analysis is 5%. However, since we are performing three pairwise comparisons between the three different experimental conditions, to reduce the chance of false negative error (error type-I), we performed a Bonferroni correction on the alpha by dividing the alpha by 3 (i.e., $alpha = \frac{5\%}{3} \approx 1.7\%$). Therefore, under the assumption of each null-hypothesis, a $p$ less than 0.017 rejects the null-hypothesis.

Also, we compared the mean values of the same statements in the three experimental conditions to calculate their possible improvement/deterioration upon each other. The improvement/deterioration is calculated with the following formula.

$$\begin{aligned} Improvement \ \ (or \ \ deterioration) &= \frac{(Mean_1 - Mean_2)}{(Likert \ \ Max \ \ Score - Likert \ \ Min \ \ Score)} \\ &= \frac{(Mean_1 - Mean_2)}{2-(-2)} \\ &= \frac{(Mean_1 - Mean_2)}{4}. \end{aligned} \tag{1}$$

*5.1.1. Attitude.* Since interacting with an interface which empathizes with the clients is a new experience for the users and provides a novel supportive way of interacting with the computer, we can expect that the clients show a more positive attitude to using the empathic counselor than the non-empathic and textual ones.

Results show significant differences in terms of attitude between the empathic and non-empathic conditions ($X^2 = 5.76$, $p = 0.016 < 0.017$); and between empathic and textual conditions ($X^2 = 9.21$, $p = 0.002 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 0.081$, $p = 0.776 > 0.017$). These results indicate that, on the one hand, a non-empathic avatar cannot improve the attitude of using a textual counseling system. On the other, when an empathic avatar is used, significant differences appear. Therefore, the clients expect a human-like system to be empathic. This result confirms previous research by Nguyen and Masthoff [2009].

The positive mean values of empathic ($mean = 0.78$, $stdev = 0.9$), non-empathic ($mean = 0.31$, $stdev = 1.05$), and textual ($mean = 0.26$, $stdev = 0.86$) versions indicate that the clients have a positive attitude toward the system and found it a good idea to use the virtual health counselor, regardless of the interface modality. However, the mean value comparison shows that the clients have 11.81% more positive attitude to use the empathic counselor than the non-empathic counselor and 13.06% more than the textual version.

*5.1.2. Intention to Use.* Results show significant differences in terms of intention to use between the empathic and non-empathic conditions ($X^2 = 6.41$, $p = 0.011 < 0.017$); and between the empathic and textual conditions ($X^2 = 16.67$, $p \approx 0.000 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 4.60$, $p = 0.032 > 0.017$). These results support the previous result that the clients expect a human-like system to be empathic [Nguyen and Masthoff 2009].

The positive mean values of empathic ($mean = 0.80, stdev = 0.89$), non-empathic ($mean = 0.12, stdev = 0.89$) show that the clients have positive intentions to use the avatar-based counselors. This result confirms the results of our previous research [Lisetti et al. 2012] in which 74% of the clients reported a positive intention to use the avatar-based system. The negative mean value of the textual version ($mean = -0.45, stdev = 1.02$) indicates that the clients have negative intentions to use the text-based counselor. The mean value comparison shows that the clients have 17.12% greater intention to use the empathic counselor than the non-empathic counselor and 31.36% greater than the textual version. Also, they have 14.25% greater intention to use the non-empathic counselor than the textual one.

*5.1.3. Perceived Enjoyment.* Nonverbal mimicry increases rapport [Lafrance 1979; Lafrance and Broadbent 1976], facilitates communication, and may increase listeners' attention [Lafrance and Broadbent 1976]. So, we can expect that the clients engage more with the empathic counselor and find it more enjoyable than the non-empathic and textual ones.

Results show significant differences in terms of perceived enjoyment between the empathic and non-empathic conditions ($X^2 = 24.40$, $p \approx 0.000 < 0.017$); and between the empathic and textual conditions ($X^2 = 26.73$, $p \approx 0.000 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 0.013$, $p = 0.91 > 0.017$). Again, it shows that the clients expect a human-like system to be empathic.

The positive mean values of empathic ($mean = 0.99, stdev = 0.63$), non-empathic ($mean = 0.31, stdev = 0.97$), and textual ($mean = 0.39, stdev = 0.88$) versions indicate that the clients perceived the system positively enjoyable, regardless of the interface modality. However, the mean value comparison shows that the clients enjoyed the empathic version 17.11% more than the non-empathic one and 15.10% more than the textual version. Therefore, the clients enjoy a textual system more than a non-empathic human-like system.

*5.1.4. Perceived Ease of Use.* Results show no significant differences between any pairs of the experimental conditions: empathic and non-empathic conditions ($X^2 = 0.52$, $p = 0.471 > 0.017$); empathic and textual conditions ($X^2 = 1.45$, $p = 0.228 > 0.017$); or non-empathic and textual conditions ($X^2 = 0.07$, $p = 0.778 > 0.017$).

The mean values of empathic ($mean = 0.84, stdev = 1.24$), non-empathic ($mean = 0.96, stdev = 1.27$), and textual ($mean = 0.82, stdev = 1.24$) versions indicate that the clients perceived all the versions easy to use; however, the clients prefer a character to help them during the interaction rather than a pure textual intervention. It seems that enabling the character to empathize with them complicates the use of the system. It is possible that users feel uneasy being watched or evaluated all the time with an intelligent ECA [Catrambone et al. 2004]. Also, users feel that the counselor understands them (see Section 5.1.5), and they get the impression that a real person is talking to them, which may make it harder for them to use the system in the presence of the counselor.

*5.1.5. Perceived Sociability.* Mimicking the facial expression and empathizing using the facial expressions of a speaker plays an important role in the perception of empathy [Sonnby-borgström et al. 2003]. So, we can expect that the empathic counselor reacts more appropriately to the clients' affective states and that clients find it more understanding and empathizing than the non-empathic counselor and the textual version.

Results show significant differences between all three pairwise versions; empathic and non-empathic conditions ($X^2 = 36.57$, $p \approx 0.000 < 0.017$); empathic and textual conditions ($X^2 = 17.58$, $p \approx 0.000 < 0.017$); non-empathic and textual conditions ($X^2 = 6.22$, $p = 0.012 < 0.017$).

Statements in the Perceived Sociability category debrief the clients about the empathizing, understanding, and social abilities of the counselor. Therefore, the positive mean value of empathic counselor ($mean = 0.80, stdev = 0.87$) indicates that the clients perceived it empathizing, understanding, nice, and sociable. On the other hand, the negative mean value of the non-empathic version ($mean = -0.07, stdev = 0.97$) and the small positive mean value of textual version ($mean = 0.26, stdev = 0.98$) indicate that the clients perceived them, respectively, 21.68% and 13.56% less sociable than the empathic version.

The users perceived the empathic counselor a more pleasant conversational partner than the non-empathic one by 19.81% (statement 14). They reported that the empathic counselor understands the users 20.65% more than the non-empathic one (statement 15). The empathic counselor was rated 21.50% nicer than the non-empathic counselor (statement 16). Most importantly, the empathic counselor was perceived 24.77% more empathic than the non-empathic one (statement 17).

*5.1.6. Perceived Usefulness.* Results show significant differences between the empathic and non-empathic conditions ($X^2 = 10.13$, $p = 0.001 < 0.017$); and between the empathic and textual conditions ($X^2 = 5.88$, $p = 0.015 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 1.36$, $p = 0.243 > 0.017$).

The positive mean values of empathic ($mean = 0.68, stdev = 0.88$), non-empathic ($mean = 0.02, stdev = 1.08$), and textual ($mean = 0.24, stdev = 0.97$) versions indicate that the clients perceived the system positively useful, regardless of the interface modality. However, the mean value comparison shows that the clients think that an empathic counselor is the most useful (16.52% more than non-empathic and 10.94% more than textual), but if a counselor is not empathic, it can be less useful than a pure textual intervention system.

*5.1.7. Social Presence.* Nonverbal mirroring helps create a smoother interpersonal interaction between partners [Chartrand and Bargh 1999], so we can expect that the clients' engagement with the empathic system would be more than the non-empathic and the textual ones.

Results show significant differences between the empathic and non-empathic conditions ($X^2 = 25.15$, $p \approx 0.000 < 0.017$); and between the empathic and textual conditions ($X^2 = 46.20$, $p \approx 0.000 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 3.26$, $p = 0.071 > 0.017$). The not-significant difference between non-empathic and textual versions and significant differences between the other two pairs support the same previous results.

The positive mean value of empathic ($mean = 0.21, stdev = 1.07$) indicates that the clients sense a a social entity when interacting with the empathic counselor. But, negative mean values of non-empathic ($mean = -0.57, stdev = 0.99$) and textual

($mean = -0.80, stdev = 0.93$) versions show that the clients do not have this sense when interacting with non-empathic and textual versions. The empathic counselor makes 19.73% improvement over the non-empathic version and 25.14% improvement over the textual version.

On the one hand, negative mean values of the non-empathic version mean that the users did not feel that they are talking to a real person (statement 20), they did not imagine the counselor as a living creature (statement 22), and they did not feel that the counselor has real feelings (statement 23).

One the other hand, the positive mean values of the empathic value show that the users perceive the counselor as a real person who is looking at them and has real feelings. The mean value in statement 22 shows that although the empathic counselor is perceived more live than the non-empathic one, it is still not perceived as a living creature.

*5.1.8. Trust.* Since empathizing with the clients is known as a good way of building trust and receiving more information from the clients, we can expect that the clients can disclose more information to the empathic counselor than to the non-empathic one.

Results show significant differences between the empathic and non-empathic conditions ($X^2 = 13.01$, $p \approx 0.000 < 0.017$); and between the empathic and textual conditions ($X^2 = 5.7$, $p = 0.0169 < 0.017$); but no significance difference between the non-empathic and textual conditions ($X^2 = 2.77$, $p = 0.096 > 0.017$).

If we look at the statements individually, the positive mean values in statement 24 indicate that the users would trust all the empathic ($mean = 0.88, stdev = 0.82$), non-empathic ($mean = 0.12, stdev = 0.93$), and textual ($mean = 0.27, stdev = 0.99$) counselors if they give them advice; however, they trust the empathic counselor 19.12% more than the non-empathic one and 15.18% more than the textual version. Also, statement 25 shows that the users would follow the advice of the empathic ($mean = 0.68, stdev = 0.84$) counselor 6.42% more than that of the non-empathic ($mean = 0.42, stdev = 0.57$) one and 12.45% more than that of the textual ($mean = 0.18, stdev = 0.97$) version.

In terms of privacy, the users prefer to interact with a human counselor rather than a non-empathic ($mean = -0.38, stdev = 1.3$) virtual counselor (statement 26). But, they prefer to interact with an empathic ($mean = 0.56, stdev = 1.06$) counselor or a textual system ($mean = 0.12, stdev = 1.15$) rather than a human counselor. Therefore, the empathic counselor improved the non-empathic counselor by 23.62%, and improved the textual version by 10.97%, as mean values show that users feel 12.65% more privacy when interacting with a pure textual system than a non-empathic counselor.

Statement 27 shows that the users believe that they can disclose more information to a human counselor than a virtual counselor delivered by a character. However, the empathic version ($mean = -0.13, stdev = 1.27$) has 7.45% improvement over the non-empathic ($mean = -0.42, stdev = 1.21$) one. And more interestingly, the users believe that they can disclose more information about their drinking to a textual system ($mean = 0.1, stdev = 1$) than a human.

Over all four statements in the Trust category, the empathic ($mean = 0.51, stdev = 1.07$) and textual ($mean = 0.17, stdev = 1.03$) versions have positive mean values, and the non-empathic has a negative mean value ($mean = -0.07, stdev = 1.01$). The overall mean value comparison shows that the empathic counselor is 14.31% more trustful than the non-empathic one and 8.46% more than the textual version.

*5.1.9. Anxiety.* Affective virtual agents can support users through stressful tasks [Gratch and Marsella 2004]. Therefore, our expectation is that the clients who use the empathic counselor feel less anxious that those who use the non-empathic version.

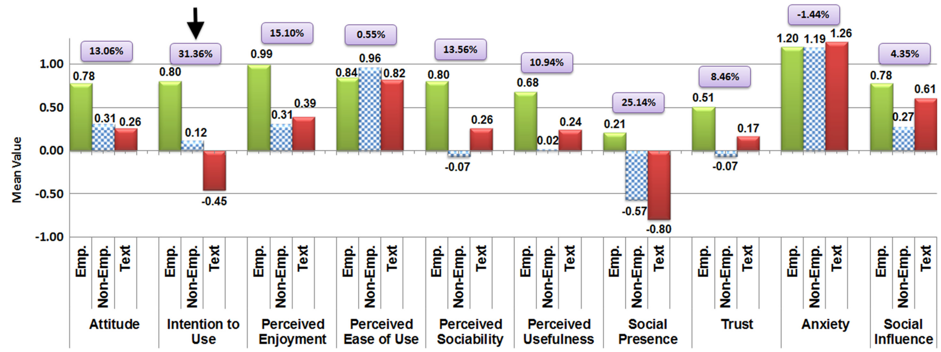


Fig. 6. Mean value comparison of experimental conditions for user acceptance features. The percentages show the empathic character's improvement over the textual system.

Results show no significant differences between any pair of the experimental conditions: empathic and non-empathic conditions ($X^2 = 0.003$, $p = 0.954 > 0.017$); empathic and textual conditions ($X^2 = 0.29$, $p = 0.591 > 0.017$); or non-empathic and textual conditions ($X^2 = 0.32$, $p = 0.573 > 0.017$).

The positive mean values of empathic ($mean = 1.2, stdev = 0.87$), non-empathic ($mean = 1.19, stdev = 1.02$), and textual ($mean = 1.26, stdev = 0.76$) versions indicate that none of the three counselor versions evoke anxiety while interacting with the clients and there are no significant improvements in the mean values. This means that the delivery modality (textual vs. character-based) and the empathizing ability (empathic vs. non-empathic) did not reduce the anxiety level of the clients during the interaction, which does not support our expectation in the beginning of this section.

*5.1.10. Social Influence.* Results show no significant differences between any pairs of the experimental conditions: empathic and non-empathic conditions ($X^2 = 5.53$, $p = 0.018 > 0.017$); empathic and textual conditions ($X^2 = 0.79$, $p = 0.373 > 0.017$); or non-empathic and textual conditions ($X^2 = 2.81$, $p = 0.0935 > 0.017$).

The positive mean values of all three versions—empathic ($mean = 0.78, stdev = 1.03$), non-empathic ($mean = 0.27, stdev = 1.10$), and textual ($mean = 0.61, stdev = 1.04$)—have positive social influence on the clients independently of the interaction modalities. The empathic counselor was reported to have 12.77% more social influence on the users than the non-empathic one and 4.35% more than the textual version.

Figure 6 shows the mean value comparison of the three experimental conditions for the user acceptance features just described.

*5.1.11. Anthropomorphism.* The visual channel facial expressions is deemed to be the most important in the human judgment of behavioral cues [Ambady and Rosenthal 1992], because human observers seem to be mostly accurate in their judgment when looking at the face. This fact indicates that people rely on displayed facial expressions to interpret someone's behavioral disposition. So, the empathic counselor is expected to be perceived more anthropomorphic and believable for the users than the non-empathic one.

Since no virtual character is used in the textual version, we do not evaluate anthropomorphism for that version. However, we compare the empathic and non-empathic versions which include an avatar. Results show that there are significant differences between the empathic and non-empathic counselors ($X^2 = 27.42$, $p \approx 0.000 < 0.017$) in terms of anthropomorphism.

The positive mean value of the empathic version ($mean = 0.28, stdev = 1.05$) indicates that the counselor was positively perceived anthropomorphic by the clients. On the other hand, the negative mean value of the non-empathic version ($mean = -0.47, stdev = 1.10$) indicates that the non-empathic version is perceived as not so anthropomorphic and is perceived 18.73% less anthropomorphic than the empathic version.

*5.1.12. Likability.* Lakin et al. [2003] believe that mimicking others' behaviors causes feelings of closeness, liking, and smoother social interactions. So, we can expect that clients like the empathic counselor more than the non-empathic and textual ones.

Results show significant differences between the empathic and non-empathic conditions ($X^2 = 21.51$, $p \approx 0.000 < 0.017$); and between the empathic and textual conditions ($X^2 = 31.58$, $p \approx 0.000 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 0.93, p = 0.334 > 0.017$). This indicates that a non-empathic avatar does not affect the likability of the system, but adding an empathic avatar affects the likability.

The positive mean values of the empathic ($mean = 1.29, stdev = 0.64$), non-empathic ($mean = 0.85, stdev = 0.78$), and textual ($mean = 0.76, stdev = 0.81$) versions indicate that the clients liked all versions of the system. However, the empathic version is 10.85% more likable than the non-empathic one and 13.11% more likable than the textual version.

*5.1.13. Animacy.* Since no virtual character is used in the textual version, we do not evaluate the animacy for that version. However, we compare the empathic and non-empathic versions, which include an avatar. Since the empathic counselor expresses different facial expressions and verbal reflections, it is expected to have a better animacy than the non-empathic one.

Results show that there are significant differences between the empathic and non-empathic counselors ($X^2 = 28.59$, $p \approx 0.000 < 0.017$). The positive mean value of the empathic version ($mean = 0.68, stdev = 0.98$) indicates that the counselor was perceived as well-animated. On the other hand, the negative mean value of the non-empathic version ($mean = -0.11, stdev = 1.21$) indicates that the non-empathic version is not perceived so well-animated: it is perceived 19.69% less animated than the empathic version.

*5.1.14. Perceived Intelligence.* Because the empathic feedbacks are provided based on the current most probable affective state of the client and her/his answers, the client may see the empathic counselor more intelligent than the non-empathic one.

Results show significant differences between the empathic and non-empathic conditions ($X^2 = 18.76$, $p \approx 0.000 < 0.017$); and between the non-empathic and textual conditions ($X^2 = 13.56$, $p \approx 0.000 < 0.017$); but no significant difference between the empathic and textual conditions ($X^2 = 1.24$, $p = 0.266 > 0.017$).

The positive mean values of the empathic ($mean = 0.93, stdev = 0.74$), non-empathic ($mean = 0.42, stdev = 1.04$), and textual ($mean = 0.82, stdev = 0.82$) versions indicate that the clients perceived all versions intelligent. However, comparison shows that the empathic and textual version are, respectively, 12.82% and 10.22% more intelligent than the non-empathic version. Therefore, adding a non-empathic avatar affects the perceived intelligence negatively, but an empathic avatar affects the perceived intelligence positively.

*5.1.15. Perceived Safety.* Mimicry has been shown to influence the emotional state of an interaction partner positively [van Baaren et al. 2004]. Also, affective virtual agents can increase client's abilities to recognize and regulate emotions and help motivate

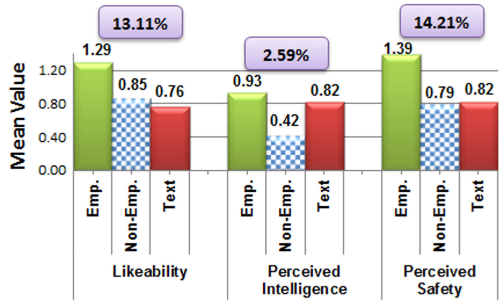


Fig. 7. Mean value comparison of experimental conditions for the character features. The percentages show the empathic character's improvement over the textual system.

users [Gratch and Marsella 2004]. So, we expect to see more positive emotions than negative ones during the interaction with the empathic counselor.

Results show significant differences between the empathic and non-empathic conditions ($X^2 = 11.44$, $p \approx 0.000 < 0.017$); and between the empathic and textual conditions ($X^2 = 10.54$, $p = 0.001 < 0.017$); but no significant difference between the non-empathic and textual conditions ($X^2 = 0.02$, $p = 0.895 > 0.017$). This indicates that a non-empathic avatar does not affect the level of perceived comfort/danger during the system use, but an empathic avatar does.

The positive mean values of the empathic ($mean = 1.39, stdev = 0.95$), non-empathic ($mean = 0.79, stdev = 1.11$), and textual ($mean = 0.82, stdev = 1.21$) versions indicate that the clients feel comfortable when using all versions of the system. However, the empathic version is perceived as 14.79% safer than the non-empathic one, and 14.21% safer than the textual version.

Figure 7 shows the mean value comparison of the three experimental conditions for the character features just described.

## 6. FUTURE WORK

Interesting paths for future research is this area which we plan to address are (1) integrating our work with nonverbal character animations, spoken dialog management, and a combination of the two in order to continue to increase the potential of On-Demand VIrtual Counselors (ODVIC) for the smart health and well-being domain; (2) studying how to simulate ethnic patient-physician concordance to increase positive health outcomes; (3) studying whether, as virtual counselors become emotionally, socially, and/or culturally competent, they will maintain, decrease, or increase people's openness and self-disclosure with computer-based health interventions; (4) evaluating our OCVIC system in terms of drinking outcomes on heavy drinkers over longer periods of time at 3-month, 6-month, and 12-month periods, similar to Hester's DCU study [Hester et al. 2005]; (5) evaluating our system in terms of dropout rates over 3-month, 6-month, 12-month periods, comparing the text-only DCU with the empathic ODVIC, and setting up the experiment with random assignments for both conditions at the same time, while gathering demographic information.

It is our hope that, as research progresses in the study of virtual characters for health interventions as well as in the development of novel healthcare and medical interventions, additional questions will arise that will bring closer to reality our vision of increasingly helpful, supportive, and likable virtual counselors. To make this happens, it is crucial that computer science and information technology experts continue to learn healthcare and medical experts' language, and vice versa. Only then will experts in each of these disciplines be able to understand the research questions and different perspectives of the others' fields and be able to truly work with the interdisciplinary spirit necessary for full success.

## 7. CONCLUSION

In this article, we have described the design, implementation, and evaluation of an empathic virtual character—ODVIC, the On-Demand VIrtual Counselor—who can deliver an evidence-based Brief Motivational Intervention (BMI) for excessive alcohol consumption behavior change, adapted from the well-established Drinker's Check-Up (DCU) [Hester et al. 2005].

Users' overall acceptance of the system over a number of dimensions regarding the impact of the empathic communication of the ODVIC character indicates that this novel modality of delivery for behavior change intervention could have a significant impact in terms of users' motivation to continue using computer-based behavior change interventions, over the long term, in order to find and maintain healthy lifestyles.

Of particular interest to us is the demonstrated increase by over 30% of user's reported intention to use the intervention delivered by the ODVIC character over the one delivered by the text-only system.

These results are very promising, particularly since it has been established that, although computer-based brief motivational behavior change interventions can truly help people toward healthy lifestyles, too many people drop out before benefiting from them. Our approach may therefore lead to systems that decrease drop-out rates of behavior change interventions, which is a significant problem with not only computer-based interventions but also with face-to-face interventions [Dunn et al. 2012; Wierzbicki and Pekarik 1993].

Furthermore, because BMIs are adaptable and our system is modular, our approach can be adapted to target behaviors such as overeating and lack of exercise, among other lifestyle behaviors. Our approach could therefore contribute to addressing several of modern epidemic behavioral issues and promote healthy lifestyles for a variety of people in need.

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