Towards building a Virtual Counselor: Modeling Nonverbal Behavior during Intimate Self-Disclosure

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ABSTRACT
Nonverbal behavior is considered critical for indicating intimacy and is important when designing a social virtual agent such as a counselor. One key research question is how to properly express intimate self-disclosure. In this paper we present an extensive study of human nonverbal behavior during intimate self-disclosure. This is an important milestone in creating a virtual counselor. A study of video interactions between human participants demonstrated that people display more head tilts and pauses when they revealed highly intimate information about themselves; they presented more head nods and eye gazes during less intimate sharing. An implementation of these behaviors in a virtual agent suggests that people tend to perceive head tilts, pauses and gaze aversion by the agent as conveying intimate self-disclosure. These findings are important for future research with virtual counselors and other social agents.

Categories and Subject Descriptors
I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents.
J.4 [**Social and Behavioral Sciences**]: Psychology.

General Terms
Experimentation, Human Factors.

Keywords
Virtual agents, Nonverbal behavior, Intimacy, Self-disclosure, Rapport, Affective behavior.

1. INTRODUCTION
Humans often share personal information with others in order to create social connections. Sharing personal information is especially important in counseling interactions [14]. Research studying the relationship between intimate self-disclosure and human behavior critically informs the development of virtual agents that create rapport with human interaction partners. One significant example of this application is using virtual agents as counselors in psychotherapeutic situations. We argue that the capability of expressing different intimacy levels is key to a successful virtual counselor to reciprocally induce disclosure in clients. Previous studies [5,6] found that human clients liked virtual counselors who disclosed personal information, only verbally. In this paper, we address the complementary challenge of learning nonverbal behavior associated to self-disclosure.

There has been substantial interest in modeling the nonverbal behavior of humans for application in developing virtual agents [4,7,8,15,16,21,24]. Patterns of nonverbal behavior have been studied in terms of a function of intimacy in social interactions [11]. Existing studies found that nonverbal behavior may indicate intimacy [2,11] by operating as a key channel for the expression of communicators' inner feelings and intentions [10,25,26]. Edinger and Patterson [11] describe that intimacy could be defined as the principal affective reaction toward the other person in interpersonal communication. Researchers further argue that nonverbal signals are more believable than verbal cues as those are impulsive and harder to be manipulated [18].

Specifically, in psychotherapeutic situations, researchers have addressed the critical role that nonverbal behavior plays in the formation and maintenance of the therapeutic relationship by shaping rapport between counselors and clients [26]. Research has found that clients' nonverbal behavior unconsciously disclosed intimate information that is not conveyed by verbal signals [14,26]. Therefore, counselors' communication with clients using nonverbal affective expression may enhance counseling effects.

Our study is an important step in building a virtual counselor. The goal of our study is to learn a model of nonverbal behavior that indicates intimacy for use by virtual counselors. Based on the literature review, our current study focuses on the investigation of humans' nonverbal behavior in association with their intimate verbal self-disclosure in interview interactions. We formulate our main research question as:

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"*What types of nonverbal behavior does a person present when s/he discloses information with different levels of intimacy?*"

To address this research question, we analyze the data of interviewees' nonverbal behavior in conjunction with their intimate self-disclosure. This dataset was collected by Kang and Gratch in the context of a study focusing on verbal self-disclosure for virtual counselor [17]. The dataset did not have an interviewer's self-disclosure but an interviewee's self-disclosure in counseling interactions. Since nonverbal behaviors form part of general human interaction patterns, we assume that the data learned from client behavior will be useful for modeling the non-verbal behavior of counselors. We focus on six nonverbal behaviors: eye gazes, head nods, head shakes, head tilts, pauses (silence) and smiles. The choice of six nonverbal behaviors was motivated by a literature review and features diagnostic of social effects in prior work [3,9,12,18,19,23,25], as well as a pre-analysis by an expert in nonverbal communication. These six nonverbal behaviors were identified as being easily recognizable with current visions system and having the most potential.

Our results show that interesting nonverbal patterns are often associated with self-disclosure, both with individual features (e.g. head nods or head tilts) and co-occurrence (e.g. head tilts and pauses). We also present an inter-coder reliability designed for continuous behavior annotations. Based on these findings, we present a preliminary study analyzing the effect of nonverbal behavior with a virtual counselor.

The following section describes the original dataset of computer-mediated one-on-one human interviews analyzing self-disclosure. This description is necessary to understand our novel analysis described in Section 3, focusing on nonverbal behavior. In section 4, we present a preliminary evaluation by applying our findings to a virtual agent. Section 5 presents discussion and conclusions.

2. SELF-DISCLOSURE DATASET

We describe in this section the details of the self-disclosure dataset used to analyze nonverbal patterns. The video sequences analyzed in our paper were recorded during the Kang & Gratch [17] study. These interviews were computer mediated (through a video conference system). In the interview interaction, the interviewee was asked to answer ten questions asked by an interviewer that required gradually increasing levels of intimate self-disclosure. We utilize the dataset[1] of the study [17] collected in the form of computer-mediated one-on-one human and interview interaction. Since interactions with virtual agents always happen through a media (e.g., computer screen), the use of computer mediation between the two humans is motivated by creating a situation that is similar to what a human experiences with a virtual agent.

[1] The human-human dataset used in this paper was part of a more extensive design involving three conditions [17].

2.1 Participants and Procedure

Thirty-six people (50% women, 50% men) from the general Los Angeles area participated in this study. They were recruited using Craigslist.com and were compensated $30 for seventy-five minutes of their participation. On average, the participants were 36 years old (M = 36.03, SD = 8.96).

The paired participants (a confederate and a subject) never met each other beforehand. The interaction took place in two separate rooms where the paired participants were placed at different times, to avoid any initial face-to-face contact. The confederate was placed in one of the rooms before a recruited subject arrived to participate in the study. Recruited subjects were given a conversational scenario where the interviewer asked ten questions requiring gradually increasing intimacy levels of self-disclosure from the interviewee. The authors of the study [17] proposed that this communication situation and the questions could motivate emotional interaction where people need to disclose personal information about themselves to get to know each other. Interviewees and interviewers in actual interactions saw each other's video image displayed on a 30-inch computer monitor (see Figure 1). Confederates played the role of an interviewer. The typical conversation was allowed to last about thirty minutes, but interviewees were not informed of any specific time limitation. The condition of the study was presented to same gender combinations of dyadic partners: male-male and female-female.

To allow video interview conversation, video conference software (Skype) and a web-cam (Logitech QuickCam Orbit MP) were used. A hands-free headset connected to the computer was provided to both of the interviewers and interviewees for the audio communication.

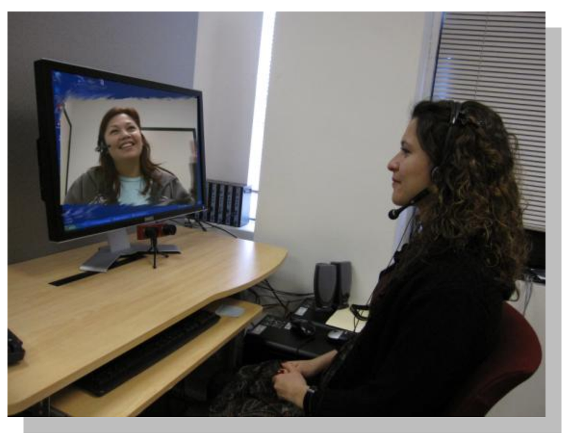

Figure 1. Computer-mediated interview interaction between an interviewer (a confederate) and an interviewee (a subject)

2.2 Measurement: Intimacy of Interviewees' Self-Disclosure

In the study [17], interviewers (confederates) did not talk about themselves, thus we decided to analyze interviewees' self-disclosure instead. The intimacy of interviewees' self-disclosure was independently rated by two coders. The coders rated verbal data of interviewees' answers from annotated audio transcriptions.

First, the two coders defined utterances as "disclosure" or "other." The utterance is "an idea unit, which is an expression of one whole idea or proposition [17]."

Second, the coders rated the intimacy level of each "disclosure" utterance using the three layer categorization scheme of Altman and Taylor's three-layer categorization scheme [1]: a peripheral layer (lower intimacy), an intermediate layer (intermediate intimacy), and core layer (higher intimacy). The examples of each category included: "I am 30-years old (peripheral layer)" "I like to go shopping (intermediate layer)" and "I feel most guilty about cheating on my girlfriend (core layer)."

After the utterances were defined as self-disclosure and intimacy levels were judged, inter-coder reliability was measured. The authors performed Krippendorff's alpha for interval data obtained by rating intimacy levels [20]. The results of Krippendorff's alpha showed good inter-coder reliability: Alpha = .84; Do (Observed Disagreement) = 232.37; De (Expected Disagreement) = 1483.14.

Therefore, interviewees' verbal self-disclosure had four intimacy levels: 0 – no intimacy, 1 – lower intimacy, 2 – intermediate intimacy, and 3 – higher intimacy. This rating scheme was used for our main data analysis described in the next section.

3. STUDY OF HUMAN BEHAVIOR: Experiments and results

Our main goal of this paper is to find what types of interviewees' nonverbal behavior is associated with different intimacy levels of verbal self-disclosure. In this section, we first describe the types of nonverbal behavior that we explored, present the inter-coder reliability of our experiments and finally discuss our findings.

3.1 Nonverbal Features

We annotated interviewees' nonverbal behavior based on the video recordings. The nonverbal features included six types of behaviors that we considered most representative features for indicating intimate self-disclosure. Details about annotating the six nonverbal features are below:

- *Eye Gazes*: Eye gazes start when an interviewee starts to look at an interviewer and ends when he or she averts his or her gaze. An annotator looked at the full sequence and identified the gaze direction associated with the interviewer, then performed the full annotation.
- *Head Nods*: Head nods are head rotations along the vertical axis (pitch angle). A head nod gesture starts when the head moves and ends when either the head stops moving or the head nod amplitude starts increasing again.
- *Head Shakes*: Head shakes are head rotations along the horizontal axis (yaw angle). They were annotated using the same approach as head nods.
- *Head Tilts*: Head tilts are head rotations within the plane defined by the torso (head rotation around the nose).
- *Pauses*: Pauses (silence) were extracted from the audio transcription files.
- *Smiles*: Smiles were annotated using the same procedure as head nods. If a smile was slowly decreasing in amplitude and suddenly increased, we annotated it as a new smile.

While nonverbal behavior was annotated for both answers and questions, the analysis presented in this paper focuses on answers annotations. We keep as future work the analysis of nonverbal behavior during questions.

We define two types of features for each annotated nonverbal behavior:

- *Normalized Duration*: Percentage of the time the nonverbal behavior was active during the answer;
- *Normalized Count*: Number of times a nonverbal behavior occurs divided by the length of the answer (in seconds).

We normalized the duration and count to remove any confounding effect caused by a big difference of the total lengths between interviewees' answers.
The annotation work was done using the ELAN software (version 3.9.0). We assigned one coder to annotate each feature, while assigning two coders for head nods and smiles as these were considered having substantial variation among coders based on the outcomes of our previous experiment.

The outcome of the inter-coder reliability analysis on head nods and smiles is presented in the next section.

3.2 Inter-Coder Reliability of Continuous Nonverbal Behavior Annotation

We calculate reliability between two coders on the annotation of head nods and smiles. Our calculation is not concerned with the individuation of gestures (for example whether a certain time span contains one or two head nods), but only with whether the annotators agree that at a certain time point a head nod occurred. We therefore treat the annotations as an aggregation of individual time slices, and check agreement on each slice separately. The raw annotations are already digitized by the maximal resolution of the annotation tool, which is 1 millisecond; for efficient computation we only look at 50 millisecond time slices -- the difference in reliability is negligible, since head nods and smiles typically last for much longer than 50ms. Observed agreement between the annotators was 95% for head nods and 84% for smiles. That is, at 95% and 84% of the time points, annotators agreed on whether or not a head nod or smile was present.

We correct for chance agreements between the annotators using Krippendorff's alpha [20], which removes the amount of agreement expected by chance. Chance-corrected agreement is 60% on head nods and 66% on smiles, showing a good amount of agreement (the figure is lower for head nods because they occur less frequently, so a higher amount of agreement is accountable by chance; overall head nods are marked 7% of the time, whereas smiles are marked 38% of the time).

There is substantial variation in the reliability of annotation for the different experiment participants. For head nods, observed agreement ranges from 86% to 99.8% (median 95%, mean 95%, s.d. 3.5%), and chance-corrected agreement ranges from -16% to 99% (median 66%, mean 62%, s.d. 25%). For smiles, observed agreement ranges from 61% to 99.1% (median 84%, mean 84%, s.d. 9.7%), and chance-corrected agreement ranges from 17% to 98% (median 67%, mean 65%, s.d. 21%). We interpret this variation as an indication that both smiles and head nods are harder to detect on some people than others. Chance correction for individual participants was always performed using the expected agreement derived from the pooled annotation data, because the larger number of observations is likely to yield a better estimate of the true amount of agreement expected by chance.

3.3 Intimacy Levels of Interviewees' Self-Disclosure

The association between interviewees' answer intimacy and their nonverbal behavior was analyzed by categorizing three levels of intimacy[2]: Low Intimacy (N = 92), Medium Intimacy (N = 91), and High Intimacy (N = 177). The Low Intimacy included "no intimacy (0)" and "lower intimacy (1)." The Medium Intimacy included "intermediate intimacy (2)." The High Intimacy included "higher intimacy (3)."

3.4 Results of Single Feature Analysis

We ran One-Way ANOVA to find the pattern of six nonverbal behaviors associated with three intimacy levels of self-disclosure: eye gazes, head nods, head shakes, head tilts, pauses and smiles.

The results showed that there was a significant difference for *Head Nods* in Normalized Duration [F(2,357) = 3.216; p = .041; η^2 = .018] for Low Intimacy (M = .088, SD = .167) and High Intimacy (M = .049, SD = .105). The results also showed a significant difference for *Head Tilts* in Normalized Duration [F(2,357) = 3.569; p = .029; η^2 = .020] for Low Intimacy (M = .039, SD = .062) and High Intimacy (M = .076, SD = .126), as well as in Normalized Count [F(2,357) = 4.465; p = .012; η^2 = .024] for Low Intimacy (M = .045, SD = .072) and High Intimacy (M = .080, SD = .122).

The results did not show statistically significant difference for other nonverbal features.

[2] The "N" indicates a total number of subjects' answers that falls into each of three categories: Low, Medium, and High intimacy.

The analysis results are presented in Table 1 and Figure 2.

3.5 Results of Co-occurrence Analysis

We are interested not only in individual features related with intimacy but also co-occurrence patterns: when two nonverbal behaviors occur at the same time. We encode these co-occurrence features the same way as individual features:

- Normalized duration: percentage of the time both features were active
- Normalized count: number of times both features were active divided by the answer length.

The results showed that there was a significant difference for *Head Nods & Eye Gazes* in Normalized Count [F(2,357) = 3.187; p = .042; η^2 = .018] for Low Intimacy (M = .089, SD = .207) and High Intimacy (M = .042, SD = .106). The results also showed a significant difference for *Head Tilts & Pauses* in Normalized Count [F(2,357) = 4.229; p = .015; η^2 = .023] for Low Intimacy (M = .024, SD = .043) and High Intimacy (M = .058, SD = .120). The results further demonstrated that there was a moderate difference for *Head Nods & Eye Gazes* in Normalized Duration [F(2,357) = 3.007; p = .051; η^2 = .017] for Low Intimacy (M = .054, SD = .121) and High Intimacy (M = .025, SD = .070).

The results did not show statistically significant difference for other nonverbal features.

Table 1. One-Way ANOVA for single features. Our analysis shows significant differences for head nods and head tilts.

	Normalized Duration				**Normalized Count**			
	Intimacy			***p***	**Intimacy**			***p***
	Low	**Medium**	**High**		**Low**	**Medium**	**High**	
Eye Gazes	.476	.415	.408	.186	.438	.338	.352	.118
Head Nods	**.088***	.051	**.049***	**.041**	.099	.074	.057	.111
Head Shakes	.066	.092	.092	.362	.038	.055	.059	.291
Head Tilts	**.039***	.054	**.076***	**.029**	**.045***	.052	**.080***	**.012**
Pauses	.462	.469	.486	.484	.733	.682	.647	.322
Smiles	.233	.300	.271	.358	.162	.167	.159	.974

*The mean difference is statistically significant by Bonferroni Test [28]

The analysis results are presented in Table 2 and Figure 3.

There was no statistically significant difference in the patterns of nonverbal behaviors associated with different intimacy levels between males and females.

Table 2. One-Way ANOVA for co-occurrence features. Our analysis shows significant difference for the patterns (i) head nods and eye gazes, and (ii) head tilts and pauses.

	Normalized Duration				Normalized Count			
	Intimacy			*p*	Intimacy			*p*
	Low	Medium	High		Low	Medium	High	
Head Nods & Eye Gazes	**.054***	.040	**.025***	**.051**	**.089***	.066	**.041***	**.042**
Head Nods & Head Tilts	.003	.003	.001	.384	.006	.007	.003	.293
Head Nods & Pauses	.052	.031	.028	.200	.084	.058	.043	.120
Head Nods & Head Shakes	.000	.000	.002	.418	.001	.000	.008	.316
Head Nods & Smiles	.019	.017	.013	.770	.035	.043	.018	.328
Head Tilts & Eye Gazes	.013	.016	.025	.128	.026	.032	.048	.260
Head Tilts & Pauses	.012	.023	.031	.085	**.024***	.038	**.058***	**.015**
Head Tilts & Head Shakes	.002	.016	.016	.299	.004	.012	.016	.221
Head Tilts & Smiles	.011	.020	.021	.553	.016	.022	.029	.384
Head Shakes & Eye Gazes	.033	.040	.039	.790	.030	.046	.046	.436
Head Shakes & Pauses	.028	.028	.034	.741	.031	.044	.052	.251
Head Shakes & Smiles	.015	.044	.033	.151	.016	.030	.029	.445
Smiles & Eye Gazes	.100	.117	.106	.810	.138	.120	.118	.776
Smiles & Pauses	.065	.083	.083	.543	.119	.124	.123	.986
Pauses & Eye Gazes	.116	.108	.129	.522	.290	.241	.242	.394

*The mean difference is statistically significant by Bonferroni Test

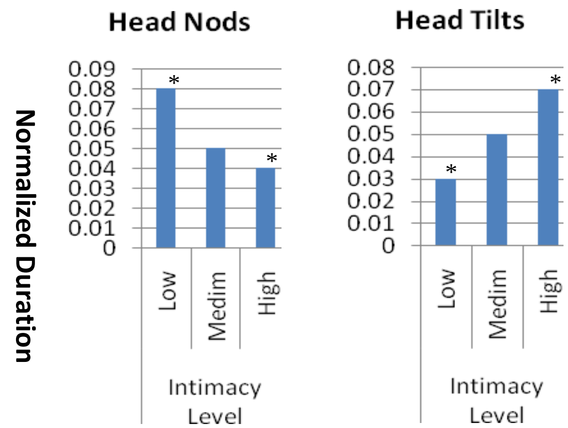

Figure 2. Mean difference of normalized duration for head nods and head tilts. We can see that head tilts are positively associated with intimacy while head nods are reduced with higher intimacy.

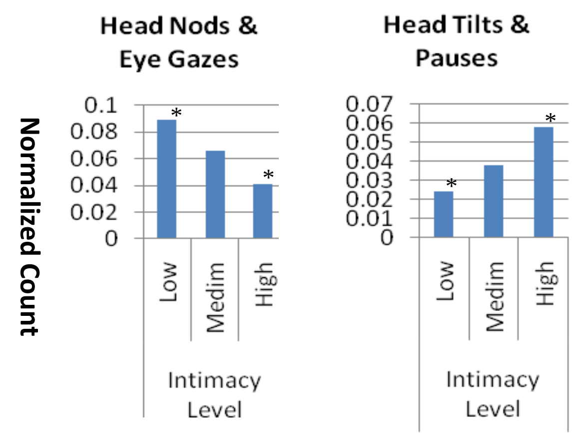

Figure 3. Mean difference of normalized count for two co-occurrence patterns. The first pattern (head nods and gazes) is inversely correlated with intimacy while the other pattern is directly associated.

3.6 Discussion

We found that interviewees showed more head tilts when they disclosed highly intimate information. Furthermore, interviewees presented more head tilts with silent pauses when they revealed highly personal information. Hesitant responses accompanied by pauses were considered unreliable reactions [11], and may mostly have been presented to avoid feelings of embarrassment that could happen when someone revealed intimate information about him or herself. These findings demonstrate that head tilts and pauses are strong nonverbal cues that convey high intimacy.

We also found that interviewees presented less head nods. Head nods are a cue of a positive response in most cultures, e.g. American culture. We contend that interviewees would hesitate to show head nods when they disclosed highly personal information, whereas they would present more head tilts as a signal of thinking to give appropriate answers in a polite manner.

Finally, head shakes and smiles were not affected significantly by intimacy levels of interviewees' self-disclosure. Head shakes are described as a feature dependent on accompanying vocal signals that imply suspicion, dissatisfaction or impossibility, while presenting "no" without saying it [18]. Therefore, head shakes are considered a signal of negative responses in most cultures, e.g. American culture. In the type of an interview interaction utilized in this study, we argue that it would not be common for interviewees to show such a negative response during their interactions with interviewers who were supposedly strangers to the interviewee. Meanwhile, smiles can be interpreted in different ways depending on social context. Smiles are usually perceived as expressions of liking and acceptance [14,27], whereas some people use smiles to hide their anxiety in a polite way [26]. Therefore, there is no right answer to interpret any finding related to the smile feature.

There was no statistically significant difference for the gaze feature, but, in general, interviewees looked at an interviewer more when they gave less intimate answers (see Table 1 & Figure 2). A similar pattern was found in the study by Exline and his colleagues [13]. They discovered that participants showed greater gaze toward an interviewer while they gave answers responding to more innocuous questions compared to more intimate ones in an interview interaction. We, however, found that interviewees showed more eye gaze accompanying head nods while interviewees were giving less intimate information about themselves (see Table 2 & Figure 3). These outcomes imply that head nods may be a strong cue representing low intimacy in communication.

The outcomes demonstrated that interviewees displayed more head tilts and pauses when they revealed highly intimate information about themselves; they presented more head nods and eye gazes during less intimate sharing.

4. IMPLEMENTATION IN A VIRTUAL HUMAN: Preliminary evaluation

We designed a short online survey to evaluate the effect of these nonverbal cues (identified in the previous section) with a virtual counselor. We hypothesized that people would perceive that a virtual counselor disclosed highly intimate self-disclosure if the counselor presented head tilts and pauses accompanied by gaze aversion.

4.1 Online survey design

In the survey, we created a webpage which included a question, a video clip, and two options to choose (See Figure 4). In the video clip, a virtual counselor was presented. The counselor disclosed highly intimate self-disclosure while demonstrating nonverbal behavior. The virtual counselor's nonverbal behavior was composed of head tilts and pauses accompanied by gaze aversion to represent high intimacy. The gaze aversion was applied to make the counselor's nonverbal behavior represent high intimacy as we found that humans showed mutual gazes and nods more for lowly intimate self-disclosure.

The final video clip was created after removing the counselor's voice so that participants would not know which words were spoken by the counselor. The video lasted fifteen seconds. As shown in Figure 4, the participants were instructed to select the spoken text that best match the nonverbal behavior of the virtual counselor. Two options were offered: low intimacy statement (option 1) and high intimacy statement (option 2). Both options were different from the spoken words by the original video, to assure that the participants could not guess based on the lip movement. The text for both options comes from validated previous work on self-disclosure [22].

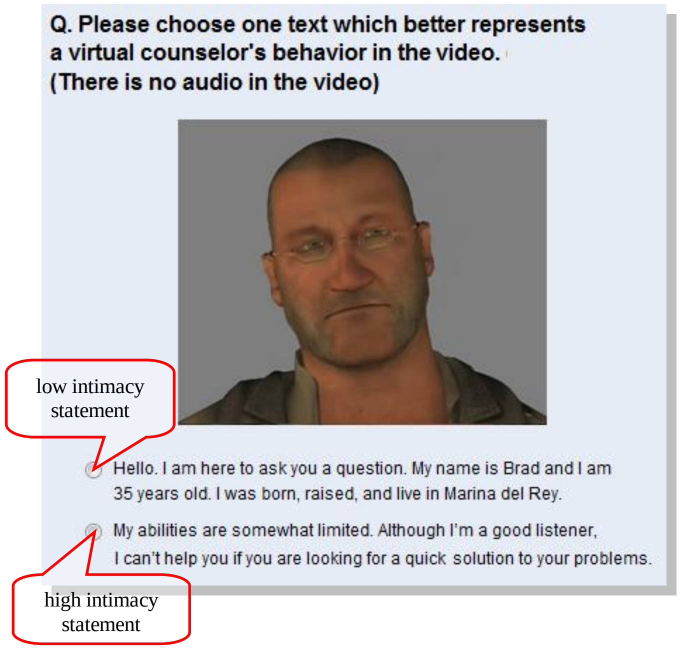

Figure 4. Web study layout. Virtual counselor displays the same nonverbal behaviors identified in our analysis (see Section 3): head tilts and pauses accompanied by gaze aversion.

4.2 Participants and Procedure

Fifteen participants (47% women, 53% men) took the survey voluntarily without any compensation. The participants were recruited via the email lists of our company and friends. On average, the participants were 27 years old (M = 27, SD = 5.0).

The participants were given the URL of the survey through an email. In the survey, participants watched a fifteen second video clip without audio and were asked to choose the spoken text that best correlates with the virtual counselor's nonverbal behavior shown in the video clip.

4.3 Results

Figure 5 shows the results of our user study. Ten participants selected the high intimacy statement while only 5 participants selected the low intimacy statement. Although still preliminary given the limited number of participants, this result is promising and gives us guidelines for the large-scale user study with a fully interactive virtual counselor.

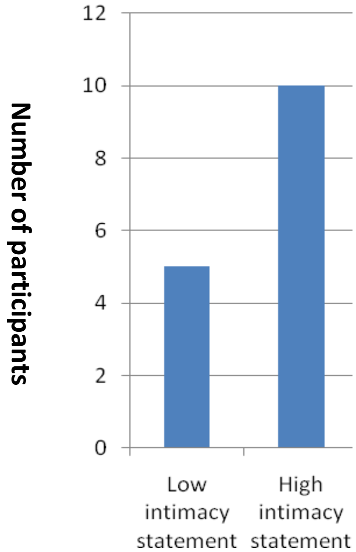

Figure 5. Results from our user study. Twice as many participants selected the high intimacy statement (option 2) over the low intimacy statement (option 1).

5. DISCUSSION AND CONCLUSIONS

Our study of nonverbal behavior in association with intimate self-disclosure provides future directions for designing virtual agents who talk about themselves during counseling interactions. Based on the outcomes of our current study, we argue that virtual counselors should show head nods and eye gazes for less intimate self-disclosure and head tilts and pauses for highly intimate self-disclosure. We contend that virtual counselors' intimate self-disclosure accompanying with appropriate nonverbal behavior will enable human clients to like their counselors more and create better rapport with them as was demonstrated by Bickmore and his colleagues [5,6] for verbal-only self-disclosure.

We presented a preliminary user study based on our findings related to intimacy and nonverbal behaviors. In the study, we focused more on finding whether users could perceive a counselor's "highly intimate" self-disclosure by looking at his/her non-verbal behaviors and associate the correct statement with the non-verbal behaviors. Our results are promising and pave the way for a large-scale user study with an interactive virtual counselor. For example, human clients will interact with the virtual counselor in counseling sessions, in which the counselor will present different types of nonverbal behavior associated with different levels of intimate self-disclosure. We also plan a future user study to look at other types of nonverbal behavior such as body movements, and the co-occurrence of more than two nonverbal behavioral features will be further investigated.

6. ACKNOWLEDGEMENTS

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