

# On the Sociability of a Game-Playing Agent: A Software Framework and Empirical Study

Morteza Behrooz, Charles Rich, and Candace Sidner

Worcester Polytechnic Institute  
Worcester, Massachusetts, USA  
{mbehrooz,rich,sidner}@wpi.edu

**Abstract.** We report on the results of evaluating a virtual agent that plays games with automatically generated social comments and social gaze. The agent played either a card game (rummy) or a board game (checkers) with each of 31 participants. Based on objective and subjective measures, the agent using social comments and gaze was preferred to both a version of the agent using only social gaze and to playing the game interactively, but without a virtual agent. We have also developed a generic software framework for authoring social comments for any game based on the semantics of the game.

**Keywords:** social interaction, social game, social comment, social gaze, virtual agent, human-robot interaction.

## 1 Introduction

It is no secret: humans love playing games. Humans have figured out a way to create games with every emerging technology in history. In fact, games have often contributed to the expansion and deployment of many of those technologies. Today, there are millions of games with different rules and goals; they are played in many different circumstances by people of different cultures and various ages. However, there is a single element in most of these gaming experiences that goes beyond these differences, an element that makes people laugh while playing games and makes them play together to enjoy more than just what the game itself has to offer: This is the *social* element of playing games.

Nowadays, the role of social robots and virtual agents is rapidly expanding in daily activities and entertainment. One of these areas is games, where people traditionally play even simple card and board games as a means of socializing, especially if not gambling. Therefore, it seems desirable for an agent to be able to play games socially, as opposed to simply having the computer make the moves in a game application.

To achieve this goal and to create a human-like experience, verbal and non-verbal communication should be appropriate to the game events and human input, to create a human-like social experience. Moreover, a better social interaction can be created if the agent can adapt its game strategies in accordance with social criteria.

To facilitate social gameplay with as many different robots, virtual agents and games as possible, we have developed a generic software framework that supports the authoring and automatic generation of appropriate social comments based on the gameplay semantics, which includes the legal moves and states of the game and an evaluation of the relative strength of particular moves and states. We applied this generic framework to a card game (rummy) and a board game (checkers) and used the resulting systems in a user study that demonstrated that users enjoy the type of social interactions that the framework supports.

In the following, after laying out the related research, we will explain study setup and procedures, followed by the results and discussions. We will then introduce our framework and describe its architecture and functionality. Lastly, we will draw conclusions and discuss future directions.

## 2 Related Work

The most closely related work to this research is by Paiva et al. [1–3], using the iCat robot. They suggest that users’ perception of the game increases when the iCat shows emotional behaviors that are influenced by the game state. They also indicate that by using affect recognition, the state and evolution of the game and display of facial expressions by the iCat significantly affects the user’s emotional state and levels of engagement. Furthermore, in a study where an iCat observing the game behaves in an empathic manner toward one of two players in a chess game, and in neutral way toward the other, the authors report on higher companionship ratings by the player to whom the robot was empathic.

The same group introduced Fatima [4], an Agent Architecture with planning capabilities designed to use emotions and personality to influence the agent’s behavior. Fatima has been used in different contexts including story-telling (e.g. FearNot! [5]) and education (e.g. ORIENT [6]). While this architecture would be extremely beneficial in bringing affect and emotion to games, it rightly has less direct focus on semantics inside the game, as it targets a general design that is suitable for many different contexts.

Paiva et al. have studied many social and emotional aspects of playing games with social robots and agents. Their work mostly focuses on empathy effects during games. While this was extremely valuable and inspiring to our research, we were more interested in focusing on the gaming side to create deeper connections between the gameplay semantics and social interactions, in a generic way.

McCoy et al. developed *Prom Week* [7], a social simulation game about the interpersonal lives of a group of high school students in the week leading up to their prom. Although in this work the virtual agents are not playing against the user, and therefore the associated social interactions are of a different nature, it clearly shows a successful application of modeling social interactions in games.

Many researchers report that social cues and emotions can make agents appear more believable. For instance, Bickmore et al. [8] report that displaying social cues by virtual agents resulted in agents being more believable in their

experiments. Also, Canamero et al. [9] and Ogata et al. [10] conclude that emotions help facilitate more believable human-robot interactions.

Gonzlez-Pacheco et al. [11] introduced a robot (*Maggie*) for playing games socially. Although their system offers a great contribution on the robotic side, including the hardware and sensory capabilities and a software platform for controlling them, it has less focus on provide a generic software framework for facilitating social interactions during games.

In [12], Van Eck notes that simple games are more suitable than complex games for establishing empathic effects, since the cognitive load on the players in such games is much lower. This observation supports our choice of simple card and board games as the initial target of our work.

Beyond gaming, there are many contexts in which sociable agents and robots are popular [13], ranging from *Keepon* [14], a minimalistic musical robot particularly useful for treating children with autism, to much more complicated social agents. Whether it is therapeutic care [15], food delivery [16] or playing with toys [17], social interactions prove to be a crucial aspect of many experiences. In this work, we study such sociability in a game context.

### 3 User Study

In our user study, a virtual agent capable of speaking comments and performing social gaze behaviors (see Fig. 1), played checkers and rummy with participants. By incorporating two different games, we intended to assess the generality of our approach and framework.

Our general assumption was that a gaming experience that involves social behaviors inspired by the semantics of the game would be preferable to a gaming experience that does not. Two readily available social behaviors were making comments and introducing some social gaze. The gaze choices for the agent were limited to ones that involved the agent directing its gaze in three different ways, but did not include mutual gaze with the user because of the complexities of assessing mutual gaze. We suspected that users' non-verbal gestures might also be important. Because smiling is associated with pleasure in playing games, we hypothesized that smiles would more readily occur when the agent produced more types of social behavior.

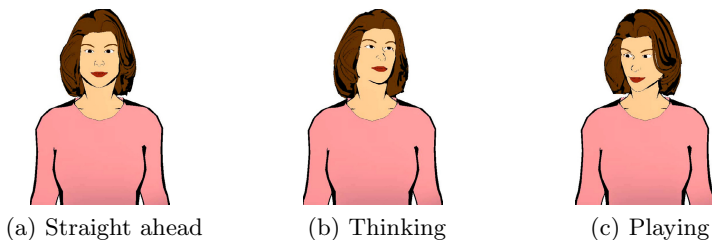
In our hypotheses below, we are exploring the relationships between social behaviors (gaze and comments) and participants' preferences and smiling.

**Hypothesis I:** Participants will (a) *prefer* and (b) *smile more* playing checkers and rummy with a virtual agent that interacts using *both* social gaze and comments, compared to *either* a virtual agent using *only social gaze* or playing *without* a virtual agent.

**Hypothesis II:** Participants will (a) *prefer* and (b) *smile more* playing checkers and rummy with a virtual agent that interacts using *only social gaze*, compared to playing *without* a virtual agent.

### 3.1 Experimental Setup

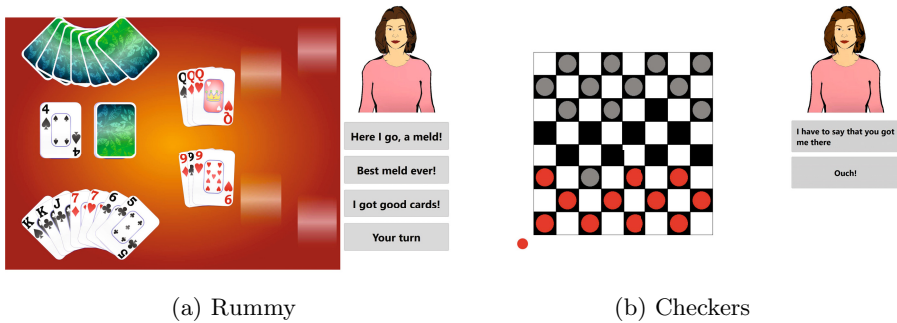
**Participants.** There were 31 participants in the study, 12 males and 19 females. The average age of participants was 20.23 with a standard deviation of 3.67. All participants were offered course credits for their participation.



**Fig. 1.** Different gaze directions of the agent

**Interaction Elements.** Our virtual agent is shown in Fig. 1. The agent was always located at the top-right part of the screen (see Fig. 2) and was able to speak and perform gazes in different directions. These gaze directions were straight ahead, thinking and playing. The thinking gaze was used before the agent played a move (for 2 to 3.5 seconds, depending on the game and move), and the playing gaze was used from 0.5 seconds before playing a move to 1 second after. The playing gaze was also used during user’s turn and before user’s move to reflect the anticipation of user’s move in agent’s expressions. A significant amount of effort was devoted to making the gaze animations and timing smooth and accurate. The rest of the time (e.g., when agent was speaking to user) the agent gazed straight ahead (during which time a face-tracking mode was activated to allow the agent’s head to follow participant’s face). During both gaze and face-tracking behaviors, the agent’s eyes moved in synchrony with its head according to well-known rules for human gaze motions.

The agent was also capable of making social comments about its own or the human player’s moves using the IVONA text-to-speech engine. After the agent’s comment, the participant is given a chance to respond by choosing one of the text menus appearing on the right side of the screen. Participants also had a chance to make a social comment on either their own or the agent’s moves, after which the agent would respond with another comment. After each played move, the commenting opportunity was given to one of the players randomly. A maximum of one comment and one optional response was possible each time. The participant had the ability to skip entering a comment, or a response, by either making a move in the game if it was his/her turn, or by selecting “*Your turn*” (Fig. 2a) which always appeared as menu choice when the agent’s turn was coming up. See Sec. 4 for details on the generic framework and how social comments were chosen.



(a) Rummy

(b) Checkers

**Fig. 2.** Complete graphical interface of the games. The text menus (in gray buttons) are offered to the users as options for commenting on the game moves, and also as options for responding to agent’s comments. Agent’s comments and responses are spoken.

**Conditions.** The study contained three conditions as follows (in all conditions the gaming area of the interface was identical):

- **NoAgent:** *The screen space occupied by the agent in the other conditions was left blank and there were no social comments;*
- **GazeOnly:** *Agent with social gaze only;*
- **GazeComment:** *Agent with social gaze and comments.*

**Procedure.** As introduced earlier, we used rummy and checkers games in our study. The study was within-subject. Each participant was assigned one of the two games and played it in all three conditions, in a random order. At the start of the study, the participant was consented by the experimenter and told which game he/she was going to play. The participant was then asked if he/she needed a tutorial about how to play that game. The tutorials were short one-page documents in electronic format that explained the game rules, but did not contain any information about the agent or the conditions. The participant was given time to read the tutorial while the experimenter waited outside.

The computer used in the study was a touch-screen PC; participants used the touch input for gameplay.

In all conditions, the participant was told that he/she had an unlimited amount of time in order to play one round of the game. However, after 7 minutes, the participant was given the option to decide to continue the game or to move on to the next phase of the study. This was primarily done to avoid the overall study time from being too long. Participants were also told to notify the experimenter by knocking on the closed door, if they finished the game sooner than 7 minutes.

After playing in each condition (during which the experimenter waited outside) the participant was asked to fill out an electronic questionnaire. The questionnaire was identical for all conditions of both games. After completing three conditions and three questionnaires, the study was concluded.

During the study, we also used the Shore [18, 19] face detection engine to record the occurrences of participants’ smiles.

**Table 1.** Questionnaire items and categories

<b>Category 1: Working Alliance Inventory (6 questions)</b>
· I can say that the opponent appreciated my gaming capabilities
· I believe that the opponent and I respect each other
· I believe the opponent was playing honestly
· I was frustrated by my interaction with the opponent in the game *
· I find our gaming experience with the opponent confusing *
· I think the opponent in the game and I trusted one another during the game
<b>Category 2: Enjoyable (5 questions)</b>
· The game was enjoyable
· I would have played the game longer
· I laughed during the game
· The game was fun
· The game was more fun than other similar computer games I have played
<b>Category 3: Sociable (5 questions)</b>
· The game was more social than other similar computer games I have played
· I felt that I had a social experience during the game
· I found the opponent in the game social
· I believe the game meant more than just winning to the opponent
· I believe the game became/was more than just winning for me
<b>Category 4: Human-like and intelligent (3 questions)</b>
· The game experience was natural and human-like
· I found the opponent in the game intelligent
· The game made me feel that I was playing with something more than just a CPU
<b>Category 5: Game adoption (5 questions)</b>
· I would show this game to my friends
· I can see myself getting used to playing this game on a daily basis
· I can see myself playing this game instead of some other more ordinary games
· I can see this game as a close replacement for playing with friends when that is not possible
· If I could, I would have asked for the same kinds of interaction in my other activities as the ones I had in the game

### 3.2 Results

**Questionnaire.** The questionnaire consisted of 24 items using a 7-point Likert scale from “strongly disagree” to “strongly agree”, coded as 1 to 7, respectively. The items were 5 different categories which were not apparent in the questionnaire. These categories, and their items, can be found in Table 1. The questionnaire items were presented in an identical shuffled order to all participants.

One of the questionnaire categories consisted of items from the Working Alliance Inventory [20], a standard collection of statements used to measure the alliance between the two parties in an interaction. *Alliance* refers to the achievement of a collaborative relationship, meaning that there is a consensus and willingness in both parties to be engaged in the interaction.

Table 2 shows the results for each questionnaire category, along with the overall results, in an aggregated fashion. The answers to the 2 items marked with asterisk in Table 1 were subtracted from 7 because of their phrasings.

**Smile Detection.** As mentioned earlier, we used the Shore [18, 19] face detection engine to detect participants’ smiles. We chose smiles because they could be reliably automated with no special apparatus for the user and also because

**Table 2.** Questionnaire results, showing the Mean and Standard Deviation (m(sd)) in an aggregated analysis over categories and overall for all conditions.  $p(x, y)$  shows the p-value from a paired two-tailed t-test between conditions  $x$  and  $y$ , where NA stands for NoAgent, GO for GazeOnly and GC for GazeComment.

Category	NoAgent	GazeOnly	GazeComment	$p(\text{NA}, \text{GO})$	$p(\text{GO}, \text{GC})$	$p(\text{NA}, \text{GC})$
1	3.86(1.72)	4.13(1.67)	4.70(1.54)	<.05	≪.001	≪.001
2	4.02(1.74)	3.99(1.77)	5.14(1.49)	.8	≪.001	≪.001
3	2.25(1.59)	2.65(1.42)	4.39(1.81)	≪.001	≪.001	≪.001
4	2.80(1.78)	3.68(1.67)	4.10(1.69)	≪.001	.07	≪.001
5	3.39(1.89)	3.65(1.59)	4.17(1.88)	.06	<.003	≪.001
aggregate	3.33(1.86)	3.64(1.71)	4.54(1.72)	≪.001	≪.001	≪.001

smiles are a facial expression associated with enjoyment in game playing. We did not have access to any other means of automatically collecting other facial expressions or body gestures that seemed relevant. In this process, Shore reported the “perceived happiness” of the participant’s facial expression as a number in the range of  $[0, 100]$ , which we recorded every 0.5 seconds. We later counted the number of times ( $h$ ) that each participant’s happiness value exceeded 50 in each condition. It should be mentioned that the creators of Shore have reported [18] a successful recognition rate of 95.3% for this feature of their engine.

We chose the threshold approach, which filters out low values in Shore’s reported numbers, as opposed to other possible methods of analysis, such as summing or averaging, to be more certain that the  $h$  value better represents smiles that were most likely caused by the game interaction and not, for example, the constant smiles of cheerful people. We did not try to correlate the timing of the smiles with any particular events in the interaction.

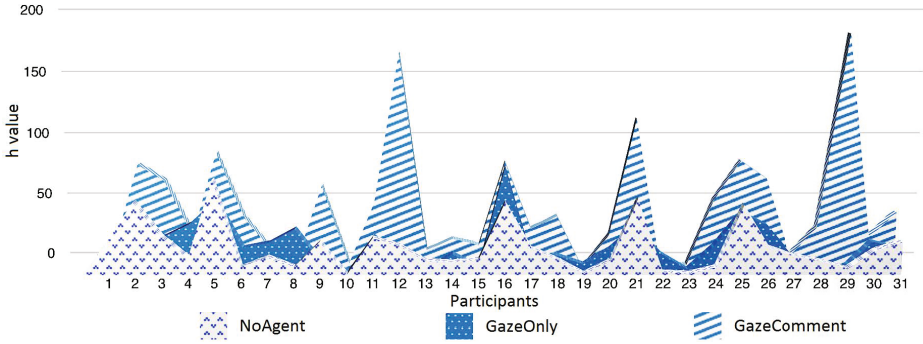
The results for a paired two-tailed t-test between the recorded  $h$  values in three conditions along with the mean  $h$  values can be found in Table 3.

**Table 3.** Mean of  $h$  values for perceived happiness in three conditions.  $p(x, y)$  also shows the p-value from a paired two-tailed t-test between conditions  $x$  and  $y$  where NA stands for NoAgent, GO for GazeOnly and GC for GazeComment.

NoAgent	GazeOnly	GazeComment	$p(\text{NA}, \text{GO})$	$p(\text{GO}, \text{GC})$	$p(\text{NA}, \text{GC})$
21.19	21.38	49.3	.9	<.002	<.001

To illustrate this distribution better, a three-dimensional area chart, showing the  $h$  values for every participant and in all conditions, can be found in Fig. 3.

Although we arbitrarily chose a threshold of 50 in our analysis, we observed that for any other threshold, ranging from 5 to 95, the average of  $h$  values in the GazeComment condition was consistently 2 to 3 times larger than that of other conditions, with similar p-values to the ones reported in Table 3.



**Fig. 3.** In this chart, the Y-axis represent the  $h$  values (with a threshold of 50) for all three conditions, while the X-axis contains each study subject (31)

**Other Results.** As stated before, participants had the chance to continue playing the game after 7 minutes. Out of 93 plays in all conditions, 41 cases were finished before 7 minutes, 46 were stopped on 7 minutes and only 6 cases were extended (3 in the GazeOnly condition and 3 in the GazeComment condition).

When the same analyses were performed for the two individual games (checkers and rummy) separately, the results of questionnaire and smile detection were similar to the combined results.

### 3.3 Discussion

Hypothesis I-a (comparing preferences for the GazeComment condition to the other two conditions) is strongly supported by the questionnaire results in Table 2, except in the case of comparing the GazeOnly and GazeComment conditions in category 4 (human-like and intelligent), for which this hypothesis remains a trend. This shows that nothing stood out for the participants in terms of agent’s intelligence and human-likeness between these two conditions. However, comparing the NoAgent and GazeOnly conditions in category 4 shows statistical significance. Thus participants’ perception of the agent’s intelligence is greater in the GazeOnly and GazeComment conditions as compared to NoAgent, even though the agent was not *really* more intelligent, since we did not change its gaming strategies. This increase hints at the importance of sociability when an agent is intended to be perceived as intelligent.

Moreover, Hypothesis I-a is also fully supported in the aggregated analysis of the questionnaire results over all categories (see Table 2).

Hypothesis I-b is strongly supported by the results as well. Smile detection analysis suggests a significant increase in the number of smile occurrences during the gaming interactions in the GazeComment condition, compared to the others.

Hypothesis II-a (comparing the NoAgent and GazeOnly conditions) is supported in the 1st (alliance), 3rd (sociable) and 4th (human-like and intelligent) categories. It remains a trend for the 5th category (game adoption) and unsupported for the 2nd category (enjoyable). On the 5th category, the results suggest



that the verbal communications are more important than the agent’s presence and social gaze in the participant’s willingness to adopt the game. Moreover, the results for the 2nd category underline the importance of verbal communications in this context. Talking is often an important element of an enjoyable social experience, especially in games, where interesting events provoke a need for verbal feedback. Furthermore, the aggregated analysis of the questionnaire results over all categories strongly supports Hypothesis II-a as well (see Table 2).

Hypothesis II-b is not supported. Smile occurrences do not show any significant difference between the NoAgent and GazeOnly conditions. This can be explained by the fact that gazes and direct looks, when not accompanied by any verbal communications, not only are not fun, but seem rather unpleasant. In fact, between humans, this kind of behavior usually bears a negative message of disengagement or dissatisfaction.

Notably, the smile detection results are consistent with the results from a related item of the questionnaire (the third item in 2nd category of Table 1) where  $p(\text{NA}, \text{GC})$  and  $p(\text{GO}, \text{GC})$  were both  $\ll .001$  and  $p(\text{NA}, \text{GO})$  was 0.8.

## 4 A Software Framework

All of the social comments in our user study were generated using a generic software framework (see Fig. 4) we developed. This framework brings to the gaming experience systematically authored social comments selected based on the semantics of the game. Since the architecture is game-independent, it enables a developer to create new social games for any robot or virtual agent. Please note that the gaze behaviors in the study were not generated by this framework. However, the study system supported BML-like markups for adding non-verbal behaviors which could be included in the commenting strings.

**A High Level Tour of the Framework.** The starting point is the *Legal Move Generator* which generates all the possible moves on every agent’s turn. Then, the *Move Annotator* annotates the generated moves with a set of pre-defined annotations that have numeric and boolean values, such as *move strength* (how much a specific move will help the player win) and *novelty* or *bluffing*. If scenarios are used (see Sec. 4.2), the annotated moves will be first filtered by the *Scenario Filter* and then the move with the highest *move strength* will be chosen by the *Move Chooser* to be played by the agent. After each played move, one of the two players will randomly be selected to make a social comment, to which the other player can respond. User’s commenting and responding options are presented as menus on the screen (see Fig. 2). In order to avoid overwhelming the user, on 25% of the moves, unless the move is significant (e.g., a double jump in checkers) or the game is in a significant state (e.g., win or lose), no comments are made. The *Comment Chooser* chooses a comment from the *Comment Library* based on the latest played move along with the *Game Logic State* (and the *Current Scenario*, if scenarios are used).

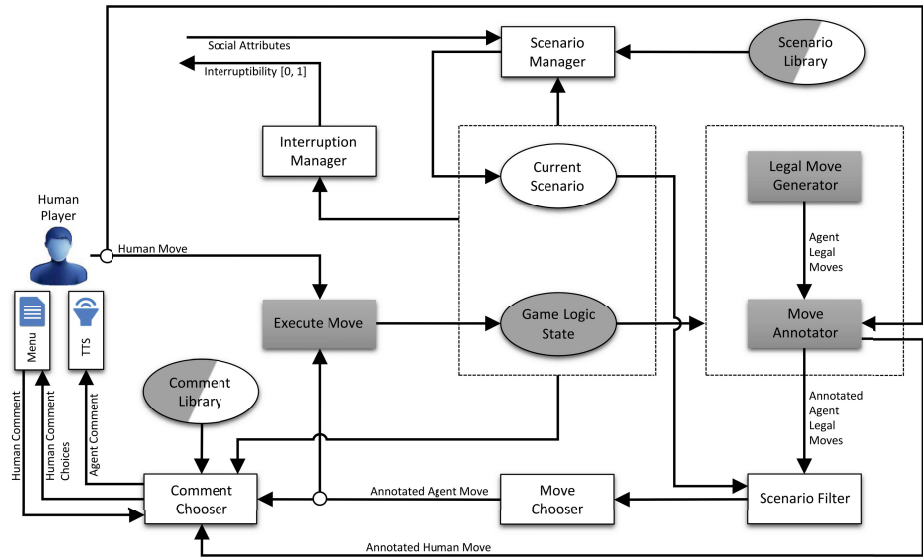
An author of a new game using this framework only has to implement the game-specific components in the architecture (gray boxes in Fig. 4) and optionally add extra generic or game-specific comments (and scenarios) to the libraries.

### 4.1 Commenting System

A main purpose of the framework is to generate social comments based on the semantics of the gameplay. This process involves the *Comment Library* and the *Comment Chooser*, which are explained below.

**Comment Library.** The *Comment Library* contains social comments authored in XML format (see Fig. 5). Each comment includes a set of attributes. Comment attributes are used to determine the best situation in which to use the comment. These attributes have boolean, numerical and string values. Examples include *competitiveness*, *regret*, *compliment*, *offensive* and *brag*. The *game-Name* attribute restricts a comment to a specific game; the *gameType* attribute restricts a comment to a specific type of game such as *card* or *board*.

**Comment Chooser.** This component chooses an agent comment or choices for the user comment menu, in response to the most recent game move or comment. For commenting on a move, an algorithm finds the best matches for the current stage of the game out of all the comment library items using the annotations of the move and the game logic state (as well as the current scenario, in case scenarios are used). These comments must have the maximum similarity in their



**Fig. 4.** Framework Architecture. Gray boxes indicate game-specific components while others are generic. Libraries have both generic and game-specific entries.

```

<comment competitiveness='0.2' tags="askHand" gameType="card" madeBy="agent"
  madeOn="agentMove">
  <content>How is your hand?</content>
  <response>Good!</response>
  <response>Not gonna tell you!</response>
  <response>Terrible</response>
</comment>
<comment competitiveness='0.3' tags="agentFewCardsLeft" gameType="card" madeBy="human"
  madeOn="agentMove">
  <content>Oh you got only a few cards left!</content>
  <response>Do not worry, too soon to tell</response>
  <response>Haha, I am gonna win</response>
</comment>
<comment competitiveness='0.8' tags="agentMeld/brag" gameName="rummy" madeBy="agent"
  madeOn="agentMove">
  <content>And that's how you make a meld!</content>
  <response>Well, wait for mine!</response>
  <response>Yes that was nice!</response>
</comment>
<comment competitiveness='0.7' tags="humanMultipleCapture" gameName="checkers" madeBy="human"
  madeOn="humanMove">
  <content>Wow! I seem to love jumping!</content>
  <response>Yea, you got me there!</response>
  <response>Oh Come on!</response>
  <response>Nice set of moves</response>
</comment>
<comment moveStrength='0.7' competitiveness='0.1' tags="humanMultipleCapture"
  gameType="generic" madeBy="agent" madeOn="humanMove">
  <content>I should say, you do play very well!</content>
  <response>Well, try to learn!</response>
  <response>Thank you, you do too</response>
</comment>
<comment competitiveness='0.6' tags="longTimeNoMeldByHuman" gameName="rummy"
  madeBy="agent" madeOn="humanMove">
  <content>You realize you have not made a meld in ages, haha!</content>
  <response>Wait for it!</response>
  <response>Yeah, I know!</response>
</comment>

```

**Fig. 5.** Sample comment library entries for generic and game specific comments. The `madeBy` and `madeOn` properties determine which player is able to use each comment, and on which player's move, respectively. The `response` fields in each comment are the response options for the player other than the one making the comment.

attributes to the most recent move's annotations and should also match certain information from the game state, such as if the game is close to the end or there are only a few cards left for a specific player. If multiple comments match the game state criteria and have equal number of matching attributes to the most recent move's annotations (with a margin or threshold for numeric values), then in case of the agent, one comment, or in case of the user, at most three commenting options are randomly chosen among the candidates. The *Comment Chooser* will initially look only among the comments with matching *gameName* and then *gameType* attributes in order to be as specific as possible.

## 4.2 Scenarios and Interruptibility

This section describes two mechanisms in the framework that were not utilized in our study, but we think may be useful in other applications that include longer-term use of our system.

*Scenarios* introduce the capability to not only control the verbal interaction in the game, but to also change the agent’s gaming strategies in order to increase its sociability. A scenario includes a plan for choosing moves with specific kinds of annotations at different stages of its progress. Thus, the agent can, for example, start the game strongly or weakly to control the suspense. Scenarios can also generate attributes for the *Comment Chooser* to enforce a desired kind of comment that fits the scenario. For example, the agent can follow a *Self-Deprecating Humor* scenario in which it starts the game strongly and then loses on purpose after generating comments with the *bragging* attribute to create a humorous experience for the user or to boost the confidence in a novice player.

In Fig. 4 the *Current Scenario* is selected by the *Scenario Manager* from the *Scenario Library* at the the start of every session. This selection is made based on a set of *Social Attributes* that are imported from outside of the framework. Thus scenarios can be used to achieve social goals in gameplay.

*Interruptibility* is continuously reported as a numeric value in  $[0, 1]$ , where a higher value is an indication of the current moment being more appropriate for pausing the game, and, for example, initiating social chit-chat on topics other than game matters (generating such chit-chat is not part of this framework). For instance, when there is nothing significant about the current game state, this value is closer to 1, whereas if a player is about to win, it is closer to 0.

## 5 Conclusions and Future Work

Our results suggest that there is a great potential in bringing sociability to the gaming interactions of virtual agents and robots, and that we can do so in a systematic way, based on the semantics of the game. We observed that this sociability significantly improved the gaming experience for users and also caused the agent to be perceived as more intelligent.

This work offers two main contributions. First, we designed and developed a generic software framework which aims at enabling many virtual agents and robots to play games socially in the future through making deeply relevant social comments based on the game state and events. Second, in order to apply and evaluate our framework, we conducted a user study, during which we observed both subjective and objective measures of the effects of social gaze and comments. The gaming interactions proved to be significantly more social, human-like, intelligent, enjoyable and adoptable when social behaviors were employed. Moreover, the participants showed increased alliance [20] with a social gaming opponent. Furthermore, since facial expressions can be a strong indication of internal state, we measured the number of participants’ smiles during the gameplay and observed that the participants smile significantly more when social behaviors were involved than when they were not.

A main limitation of our work may be the type of games used. Some more social but highly verbal games, such as charades, are perhaps beyond this approach. However, more complex games than rummy and checkers, such as Risk or Monopoly, would be worthwhile exploring in this framework.

It would also be valuable to explore if the scenarios and interruptibility in our framework (see Sec. 4.2) can influence gaming interactions and especially users' perception of the agent's sociability and intelligence.

Another interesting future direction for this work is to use emotion modeling techniques (as in [2]) for generating our social comments, so that they are able to make use of the relation between different emotional states of the users and emotional expressions of the agent, in the presence of varying gaming events. This direction will be able to take good advantage of the scenario functionality of our framework (see Sec. 4.2).

Moreover, detecting and analyzing other facial expressions than smile could be worth investigating. Furthermore, this work could be expanded for games involving more players, including one or more agents. Lastly, using an expressive robot (e.g., Reeti in Fig. 6) could lead to new opportunities.



**Fig. 6.** Reeti

**Acknowledgments.** This work is supported in part by the National Science Foundation under award IIS-1012083. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Thanks to Prof. Tim Bickmore of Northeastern University for allowing us to use their virtual agent Karen in our user study. Also, thanks to Prof. Jeanine Skorinko of Worcester Polytechnic Institute for their help in recruiting participants.

## References

1. Leite, I., Martinho, C., Pereira, A., Paiva, A.: iCat: an affective game buddy based on anticipatory mechanisms. In: Proc. of the 7th Int. Joint Conf. on Autonomous Agents and Multiagent Systems, pp. 1229–1232 (2008)
2. Leite, I., Pereira, A., Martinho, C., Paiva, A.: Are emotional robots more fun to play with? In: The 17th IEEE Int. Symposium on Robot and Human Interactive Communication, pp. 77–82. IEEE (2008)
3. Castellano, G., Leite, I., Pereira, A., Martinho, C., Paiva, A., McOwan, P.W.: It's all in the game: Towards an affect sensitive and context aware game companion. In: 3rd Int. Conf. on Affective Computing and Intelligent Interaction, pp. 1–8. IEEE (2009)
4. Dias, J., Mascarenhas, S., Paiva, A.: Fatima modular: Towards an agent architecture with a generic appraisal framework. In: Proc. of the Int. Workshop on Standards for Emotion Modeling (2011)
5. Paiva, A., Dias, J., Sobral, D., Aylett, R., Woods, S., Hall, L., Zoll, C.: Learning by feeling: Evoking empathy with synthetic characters. *Applied Artificial Intelligence* 19(3-4), 235–266 (2005)
6. Aylett, R., Vannini, N., Andre, E., Paiva, A., Enz, S., Hall, L.: But that was in another country: agents and intercultural empathy. In: Proc. of the 8th Int. Conf. on Autonomous Agents and Multiagent Systems, vol. 1, pp. 329–336 (2009)

7. McCoy, J., Treanor, M., Samuel, B., Mateas, M., Wardrip-Fruin, N.: Prom week: Social physics as gameplay. In: Proc. of the 6th Int. Conf. on Foundations of Digital Games, pp. 319–321. ACM (2011)
8. Bickmore, T.W., Picard, R.W.: Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human Interaction* 12(2), 293–327 (2005)
9. Cañamero, L., Fredslund, J.: I show you how I like you - Can you read it in my face? *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* 31(5), 454–459 (2001)
10. Ogata, T., Sugano, S.: Emotional communication robot: Wamoeba-2r emotion model and evaluation experiments. In: Proc. of the Int. Conf. on Humanoid Robots (2000)
11. Gonzalez-Pacheco, V., Ramey, A., Alonso-Martin, F., Castro-Gonzalez, A., Salichs, M.A.: Maggie: A social robot as a gaming platform. *Int. Journal of Social Robotics* 3(4), 371–381 (2011)
12. Van Eck, R., Global, I.: Gaming and cognition: Theories and practice from the learning sciences. *Information Science Reference* (2010)
13. Fong, T., Nourbakhsh, I., Dautenhahn, K.: A survey of socially interactive robots. *Robotics and Autonomous Systems* 42(3), 143–166 (2003)
14. Kozima, H., Michalowski, M.P., Nakagawa, C.: Keepon. *Int. Journal of Social Robotics* 1(1), 3–18 (2009)
15. Shibata, T.: Importance of physical interaction between human and robot for therapy. In: Stephanidis, C. (ed.) *Universal Access in HCI, Part IV, HCII 2011*. LNCS, vol. 6768, pp. 437–447. Springer, Heidelberg (2011)
16. Lee, M.K., Forlizzi, J., Rybski, P.E., Crabbe, F., Chung, W., Finkle, J., Glaser, E., Kiesler, S.: The Snackbot: Documenting the design of a robot for long-term human-robot interaction. In: *Int. Conf. on Human-Robot Interaction*, pp. 7–14. IEEE (2009)
17. Steels, L., Kaplan, F.: Aibo's first words: The social learning of language and meaning. *Evolution of Communication* 4(1), 3–32 (2002)
18. Ruf, T., et al.: Face detection with the sophisticated high-speed object recognition engine (SHORE). In: *Microelectronic Systems*, pp. 243–252. Springer (2011)
19. Küblbeck, C., Ernst, A.: Face detection and tracking in video sequences using the modifiedcensus transformation. *Image and Vision Computing* 24(6), 564–572 (2006)
20. Horvath, A.O., Greenberg, L.S.: Development and validation of the working alliance inventory. *Journal of Counseling Psychology* 36(2), 223–233 (1989)