Do Prospect-Based Emotions EnhanceBelievability of Game Characters? A CaseStudy in the Context of a Dice Game

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Abstract[1]

To endow game characters with more realistic affective behavior, the notion of prospect-based emotions plays an important role: recent literature suggests that emotional states of such agents should not only be triggered by present stimuli, but also by anticipation on future stimuli, and evaluation of past stimuli in the context of these anticipations. Within the current study, an extension of the belief-desire-intention (BDI) model with prospect-based emotions is proposed, and is evaluated with respect to its capabilities of enhancing believability of game characters. The model has been implemented in the modeling language LEADSTO. In addition, a game application has been developed, in which a user can play a two games (tic-tac-toe and a game of dice) against an agent that is equipped with the emotion-based model. An empirical evaluation indicates that the model significantly enhances the agent's believability, in particular concerning its involvement in the situation.

Keywords: prospect-based emotions, game characters, believability, evaluation.

1. Introduction

When playing games, we often show our emotions. No matter whether the game in question is a simple card game or the soccer world cup final, the people involved in such games often literally go through an emotional rollercoaster of happiness, sadness, frustration, fear, and the like. The assumption behind the current research is that human beings that play games find it natural to observe such emotions also in their game opponents. One step further, when humans play games against computer opponents, it is expected that game characters that show emotions are perceived as more human-like (or *believable* [3, 28]) than game characters that do not show such emotions, which in turn might also have a positive impact on the experienced game play. This hypothesis is exactly the topic of the research presented in the current paper. We want to test to what extent game characters that show emotions enhance believability and experience in computer games. A believable character is defined by Bates [3] as 'one that provides the illusion of life and thus permits the audience's suspension of disbelief', and to realize this, emotion is claimed to play an important role. As explained below, our focus is on emotions that are based on *expectations*, sometimes called *prospect-based emotions* [12, 22, 29].

When evaluating the impact of emotions on computer game characters, a first requirement is to have a computational model of emotions, which can be easily incorporated in the game characters. In the last decade, within the areas of Artificial Intelligence and Cognitive Modeling, various approaches have been proposed to endow Intelligent Virtual Agents (IVAs) [38] with emotions [3, 4, 15, 17, 18, 27, 32, 33, 42]. The motivation for doing this is almost commonly accepted these days: emotions allow IVAs to have more human-like appearance, to be more expressive in their behavior, and facilitate their interactions with humans [3]. By enhancing the capability of an agent to emotionally express itself, the human will more easily identify him- or herself with the agent, and possibly anthropomorphize the agent or empathize with it. In short: emotions make IVAs more believable to the humans interacting with them [3, 28].

Recently, much research has been dedicated to developing IVAs with more realistic graphical representations. However, the actual underlying affective *behavior* of such agents often stays a bit behind. For example, although many IVAs nowadays have the ability to somehow show different emotions by means of facial expressions, it is rather difficult for them to show the right emotion at the right moment. This is in conflict with the requirement of virtual agents to closely mimic human affective behavior. Nevertheless, several studies in Social Sciences have shown that this is an important prerequisite for an agent to increase human involvement in the virtual environment; see e.g. [21]. Therefore, existing systems based on IVAs are not as effective as they could be.

A particular type of emotions that is only marginally developed in many IVAs is the category of *prospect-based emotions*, like hope and fear [12, 22, 29]. Although most IVAs nowadays exploit detailed mechanisms to generate emotions based on the stimuli that are currently present (e.g., happiness and sadness) [3, 4, 15, 17, 18, 27, 32, 33, 42], their ability to generate emotions on the basis of stimuli that may occur in the future is often much less developed. This is an important difference with the affective behavior of humans, whose emotional states are constantly influenced by an evaluation of the future possibilities to fulfill their present goals [22, 29, 40]. For example, a person that desires her favorite soccer team to win will be enthusiastic if she expects that this will indeed happen, but will become frustrated if the chances for this to happen become lower (e.g., when the team is behind).

Within our current study, a generic computational model for elicitation of prospect-based emotions is presented, and is evaluated with respect to its capabilities of enhancing believability of game characters. The model was built using the high-level agent-based modeling language LEADSTO

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[9]. The model itself is not particularly innovative, but was chosen because it is generic, light-weight, and intuitive, which makes it easy to incorporate it within various real-world applications. Moreover, the model was inspired by some of the well-known emotion models in the field, such as [11] and [17, 18].

Based on this model, the main challenge of the current study is to investigate how the use of prospect-based emotion impact the way human beings perceive the game characters that show these emotions. We expect that games are a particularly suitable domain, since they usually involve very explicit goals (e.g., winning the game), expectations (e.g., winning or losing a particular phase in the game), and prospect-based emotions (e.g., hope or fear). For example, a poker playing agent that expresses its excitement because it is likely to beat the human (or expresses its sadness because it does not see any chance to win) will probably be perceived as more believable than an agent without such behavior. During the evaluation, the emotion model has been applied to two real-world applications. These applications involve a virtual opponent agent in the context of two gambling games, namely the game of tic-tac-toe and the dice game '2500'.

The outline of this article is as follows. First, in Section 2, an overview is provided of the state-of-the-art in emotion modeling for virtual agents. Next, our model for elicitation of prospect-based emotions is described in Section 3. The model is based on the LEADSTO modeling environment [9], of which details are provided in Appendix A. In Section 4, some simulation traces generated using the LEADSTO software are presented. In Section 5, the two developed game applications are discussed. Section 6 presents the experimental setup used to evaluate the model in the context of one of the applications (the dice game); the results of the experiment are presented in Section 7. Section 8 concludes the paper with a discussion.

2. Related Work

In recent years, the amount of approaches to enhance believability of virtual agents by incorporating affective processes has virtually exploded [4, 5, 15, 17, 18, 27, 32, 33, 42],. Since it is impossible to provide a complete overview of all of these approaches, we will only mention a subset of those approaches that are most closely related to our model.

One of the most influential approaches regarding emotion modeling is the computational model EMA (EMotion and Adaption) [17, 18]. Within this model, an agent perceives the world and appraises it based on utilities of states, which represent the states' desirability and importance, similar to our approach. Future expected states have probabilities, and coping strategies are used to handle the appraised expected states. Emotions emerge based on the appraisal of these states, both for the present and the future. The emotions used in EMA are joy, distress, hope, fear, anger and guilt.

As will be explained in detail in Section 3, our model follows a similar approach. In particular, we also address the emotions joy (or satisfaction), distress (or dissatisfaction), hope and fear. In addition, we will also address the emotions surprise, relief and disappointment. These last three emotions are taken from [11], which provides a logical theory of prospect-based emotions, built upon BDI notions.

The idea of applying affective modeling approaches in game contexts has also been investigated by various authors in the past. These studies include domains like poker [15], chess [32], card games [4], puzzle games [25], and even virtual soccer [7]. The affective models underlying all of these approaches differ from ours in several respects. For example, [15] uses prospect-based emotions, but no fear and relief, [4] and [32] use different hope and fear functions, and [7] and [25] use no explicit hopes or fears. On the other hand, these approaches propose some ideas that may be useful extensions to our approach, such as the influence of a long term mood, and the distinction between 'primary' and 'secondary' emotions.

Furthermore, an alternative approach to enhance agent believability is to introduce empathic emotions. Empathy is commonly defined as the capacity to "put yourself in someone else's shoes to understand her emotions" [30]. This has been investigated in detail in [27], and also in [31, 35, 37]. Research in this field shows that interaction with empathic agents enhances human-computer interaction and makes the agent more likeable. According to this research, empathic agents are perceived as significantly more caring, likeable, trustworthy and submissive. Within [27], incongruous emotions are used within an experiment with empathic agents, and it was found that participants perceive an agent with empathic emotions more positively and an agent with incongruous emotions more negatively. Although our agent is competitive rather than empathic, we expect that several of the results concerning believability found in [27] will be reproduced within our experiments.

Finally, in [1, 13, 23, 44], logical models of emotion are presented, which include prospect-based emotions. For example, in [44] an extensive formalization of emotions is put forward in the KARO framework, which consists of a combination of dynamic and epistemic logic, extended with modal operators. In [1], a formalization of the emotions of the OCC model [29] is made in BDI logic. In [23] a logical formalization of counterfactual emotions is proposed based on the psychological theory described in [46] which includes, among others, the emotion types 'disappointment' and 'elation' (which has similarities to 'relief'). And in [13], a logical analysis of emotions is described that includes a means to formalize the intensity of prospect-based emotions like hope and fear, as well as corresponding coping strategies (such as wishful thinking, positive reinterpretation and intention revision). Like these four models, the model presented in the current paper is also based on a logical language with a formal semantics (namely LEADSTO [9]). With [13] it shares the aim to express the intensity of emotions as a function of the intensities of cognitive states like beliefs and goals. However, an additional feature of the LEADSTO language is that it yields a model that is directly executable, which makes it possible to plug it in within real-world applications.

To conclude, a large number of emotion models are currently available, each with its own advantages and drawbacks. It is therefore important to mention that we do not intend to claim that the presented model is better than alternative models in the field. Rather, we defined a generic, light-weight model that is representative for a number of the more influential emotion models around, and that can easily be used within evaluation experiments. A detailed description of our model will be provided in Section 3. Nevertheless, the question which of the above approaches yields better results (and in which circumstances), is outside the scope of this article. For a discussion about this topic, the interested reader is referred to [6].

3. Model of prospect-based emotions

As a basis for the development of our model of prospect-based emotions, among others, the logical theory presented in [11] was taken. The main idea of that theory is that prospect-based emotions can be derived on the basis of several elementary concepts, among which *desires* (e.g., "I desire that it will be sunny tomorrow"), *expectations* (e.g., "it will probably rain tomorrow"), and *beliefs* (e.g., "it is sunny"). In this paper, we adopt the same approach, where we treat expectations as a specific type of beliefs (namely uncertain beliefs about the future). As such, the theory can be seen as an extension of a BDI approach [16, 39], or rather, an EBDI (emotion-belief-desire-intention) approach [1, 33].

For a global overview of the model, see Figure 1. In this picture, the dotted box indicates an agent, the boxes indicate different states, and the arrows indicate causal relationships. Note that the beliefs play different roles (see the different numbers in Figure 1):

1) Beliefs may influence desires.
2) A desire, in combination with the belief that a particular action fulfils this desire, leads to the intention to perform that action.
3) An intention to perform a particular action, in combination with the belief that it is possible to perform that action, leads to the actual execution of that action.
4) A desire for a particular state, in combination with the belief that that state may occur (an expectation), leads to a prospect-based emotion[2]. For example, if an agent desires to gain points and believes that there is a fair probability to gain points, then it will start hoping.
5) A desire for a particular state, in combination with the belief that that state has or has not occurred, leads to a prospect-based emotion.

Note that in item 4) and 5), two different types of prospect-based emotions are distinguished: emotions that appear *before* a particular (world) state or event has occurred, and emotion that appear *after* such a state has occurred. In this paper, both types of prospect-based emotions are modeled. For convenience, they will be described as *before-emotions* and *after-emotions* in the remainder of this paper.

Below, first some details of the LEADSTO language, which was used as basis for our model, are given in Section 3.1. Next, an overview of the domain ontology used for our model is provided in Section 3.2. After that, Section 3.3 explains how before-emotions are formalized in our model, and Section 3.4 provides a discussion about the particular shape of the emotion intensity function used. Based on this discussion, Section 3.5 introduces the idea of using a 'flexible' emotion intensity function. After that, Section 3.6 will address after-emotions, and Section 3.7 will discuss the impact of emotions on actions. In principle, it also possible that emotions influence other mental states (e.g., as in various coping strategies), but this is not the focus of the current paper. More formal details about the model can be found in [47].

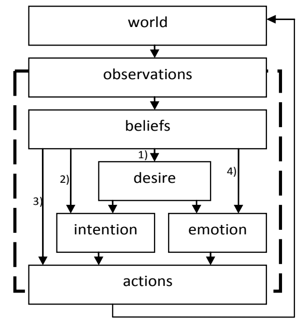

Figure 1: Overall EBDI architecture.

3.1. The LEADSTO language

Dynamics can be modeled in different forms. For example, according to the Dynamical Systems Theory (DST) [36], dynamics are modeled by continuous state variables and changes of their values over (continuous) time. In particular, systems of differential or difference equations are used for this type of modeling. This works well in applications where the world states can be modeled (in a quantitative manner) by real-valued state variables, and where the world's dynamics shows continuous changes in these world states, which can be modeled by mathematical relationships between real-valued variables. However, not for all applications dynamics can be modeled in a quantitative manner as required for DST. Sometimes qualitative changes form an essential aspect of the dynamics of a process. For example, to model the dynamics of reasoning processes, usually a quantitative approach will not work. In such processes, states are characterized by qualitative state properties, and changes by transitions between such state properties. For such applications, often qualitative, discrete modeling approaches are advocated, such as variants of modal temporal logic [26]. However, using such non-quantitative methods, the more precise timing relations are lost too.

LEADSTO is a hybrid modeling language that integrates quantitative and qualitative aspects within one representation format. In Appendix A, the structure and semantics of LEADSTO are described.

3.2. Domain ontology

An overview of the atomic state properties used in the current paper, as well as an explanation of their meaning, is provided in Table 1. In this table, the terms written in italics in the right column indicate *sorts*. Here, *importance* and *probability* are sub-sorts of the standard sort *real* (for which the values are taken between 0 and 1), and *state*, *action*, and *variant* are domain-specific sorts, for which the elements can be filled in depending on the application. For example, the sort *state* could be defined as follows:

[2] Note that we do not claim that all possible emotions (and their effects) are modeled; we only address the expectation-based emotions introduced in [11], and their impact on actions to be performed, which is considered sufficient for the current purposes.

STATE: {sunny, cloudy, rain}

All terms used in the left column are relations between sorts in the sense as explained in Appendix A. For example, the first row indicates that the relation

desire : STATE x REAL

is part of the domain ontology.

Table 1: Domain ontology

STATE PROPERTY	DESCRIPTION
desire(s,i)	the agent desires *state* s to become true with an *importance* i
belief(s)	the agent believes that *state* s is true
expectation(s,p)	the agent expects *state* s to become true with a *probability* p
previous_expectation(s,p)	the agent previously expected *state* s to become true with *probability* p
hope(s,i)	the agent experiences hope that *state* s becomes true with *intensity* i
surprise(s,i)	the agent experiences surprise that *state* s became true with *intensity* i
satisfaction(s,i)	the agent experiences satisfaction that *state* s became true with *intensity* i
dissatisfaction(s,i)	the agent experiences dissatisfaction that *state* s became true with *intensity* i
relief(s,i)	the agent experiences relief that *state* s became true with *intensity* i
disappointment(s,i)	the agent experiences disappointment that *state* s became true with *intensity* i
intention(a)	the agent intends to perform *action* a
perform(a,v)	the agent performs *variant* v of *action* a

In the following subsections, these state properties are used as part of the LEADSTO rules that make up our model for prospect-based emotions.

3.3. Emotions before an event

Following [11], two basic types of before-emotions are considered within the presented model: *hope* and *fear*. According to [11], the concept of hope can be defined in terms of desires and expectations, or, more specifically, in terms of the *importance* of a desire (sometimes called the utility) and the *probability*[3] (or likelihood) of an expected future state. Other authors take a similar approach (e.g., [17, 18, 42, 44]). In LEADSTO, the hope function is formalized as follows (note that the timing parameters e, f, g, h (see Appendix A) have been omitted, for simplicity, and that the variable s indicates the state that the emotion 'is about'):

Hope Function
$\forall$s:state $\forall$p:probability $\forall$i:importance
expectation(s, p) $\wedge$ desire(s, i)
$\twoheadrightarrow$ hope(s, f(p, i))

In this formula, the intensity of hope (which is represented as a real number between 0 and 1) is formalized by f(p, i), which stands for 'some function of probability p and importance i'. The exact shape of the function is left unspecified in this section. As explained in the next section, different equations are used in the literature to fill in this function (see [19] for an extensive discussion). By keeping the details of the hope function open, the modeler has the freedom to select her own preferred mathematical formula on the basis of the context and modeling purpose. Within the current paper, a cosine function has been used (see Section 3.4 and 3.5).

In addition to hope, the emotion *fear* is used. Similar to [11], in this paper, fear (or 'worry') is modeled as the complement of hope[4]. Thus, when an agent hopes, for instance, that it will be sunny with an intensity of 0.7, it simultaneously fears that it will not be sunny with an intensity of 0.7.

3.4. Shape of the hope curve

As explained above, the shape of the curve that describes the intensity of hope as a function of the importance of a desire and the probability of an expected future state has to be filled in for a particular application. In the literature on prospect-based emotions, different functions have been proposed for this purpose. According to most psychological theories of prospect-based emotions (e.g., [29, 40]), the intensity of hope with respect to a given event is a monotonically increasing function of the desirability and probability of the event (and analogously for the intensity of fear). As explained in [19], most computational models of emotion have been inspired by these theories in the sense that they provide specific equations that predict how appraisal variables impact the *intensity* of an emotional response. However, the exact form of these equations differs. Gratch et al. [19] classify existing models according to the following categories (each with its own generalized equation type): expected utility models, expectation-change models, threshold models, additive models, and hybrid models. In addition, they report an empirical study that was performed to compare the accuracy of these (competing) models in predicting human emotional responses in naturalistic emotion-eliciting situations (in the context of a battleship game). Some of their results are depicted in Figure 2. This figure shows the self-reported emotional intensity of four different groups (which were created by dividing subjects into equal groups based on their initial desire to win) as a function of winning likelihood. This winning likelihood was based on the stage of the game, of which the development was manipulated (i.e., participants were winning or losing dependent on the condition allocated to them).

For our current purpose (i.e., to determine an appropriate shape for the hope curve), we have a particular interest in Figure 2b). This graph suggests, in the first place, that the intensity of hope roughly increases monotonically as a function of utility (or importance), which is consistent with the literature. However, regarding the question how that the intensity of hope changes as a function of probability, the graph does not seem to be fully conclusive. In some cases (i.e., the two conditions with the highest utility) the curve seems to be monotonically increasing (except for the case where probability = 100, where it slightly decreases),

[3] Note that, instead of probability, in [11] the notion of credibility is used. Both concepts can easily be mapped: when probability is either very low (0) or very high (1), then credibility is high. When probability is around 0.5, then credibility is low.

[4] For a detailed discussion about the definition of 'fear' and its relation to hope, see [14].

whereas for the other conditions, the curve does not seem to be monotonically increasing.

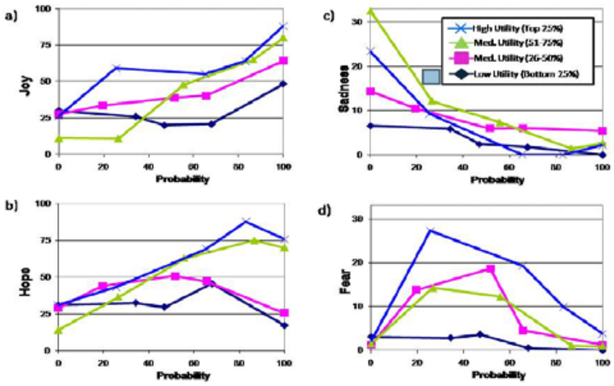

Figure 2: Self-reported emotional intensity as a function of probability and utility of goal attainment. (taken from [19])

In order to gain more insight in the shape of the hope curve, a small pilot experiment was performed. In this experiment, 15 participants were asked to imagine that they were playing a game in which they could win money on the basis of the outcome of rolling a dice. Importance was manipulated by varying the amount of money at stake (either 10, 1000 or 100.000 Euros), and probability was manipulated by changing the condition in which they would win the money, The following five conditions were used: throwing a '7' (probability=0), throwing a '1' (prob=0.16), throwing an even number (prob=0.5), throwing a '2', '3', '4', '5', or a '6' (prob=0.83), and throwing a '1', '2', '3', '4', '5', or a '6' (prob=1)). For different conditions, participants were asked to report how they would rate the intensity of their state of hope for a good result of the dice. The instructions provided to the participants are included in Appendix B.

Figure 3 displays the self-reported intensity of hope for three different conditions (characterized by the amount of money that could be won) as a function of winning probability.

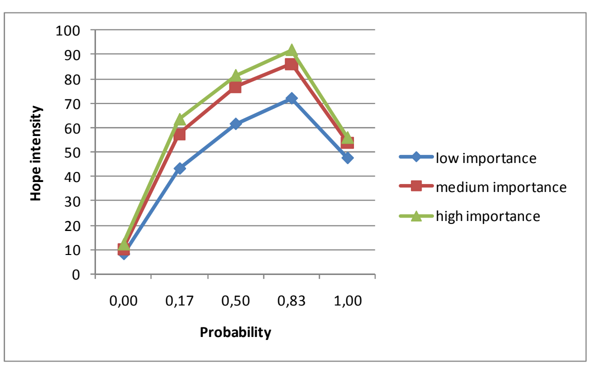

Figure 3: Self-reported intensity of hope as a function of probability and importance in the pilot experiment

Again, as in Figure 2, the results confirm that the intensity of hope increases monotonically as a function of importance (or utility). Regarding the relation between hope intensity and probability, an interesting phenomenon can be observed. At first sight, the curves seem to be monotonically increasing for all points, expect for the point where probability=1. At this point, the reported intensity of hope is around 0.5. However, if we inspect the individual answer provided by the participants in more detail, there seems to be a large variation in the answers given for this point: some participants reported hope intensities of almost 100%, whereas others were close to 0%. Apparently, the word 'hope' can be interpreted in two different ways in the case it addresses an event that is (almost) certain (such as in the case that a participant will receive money if she rolls the number '1', '2', '3', '4', '5', or '6'). Some of the participants interpret such events as invoking maximal hope, whereas others interpret them as not worth hoping for at all. This latter interpretation of hope corresponds to the view that, for hope to play a role of importance, there has to be at least some degree of uncertainty regarding the realization of the event. For instance, Snyder and colleagues state the following: "*If a goal is truly unattainable, then retaining it almost always demoralizes a person. Conversely, if attainment is perceived as certain, then the accompanying motivation typically will be low*" [43].

To analyze the results shown in Figure 3 in more detail, the participants have been grouped (post hoc) based on the difference of their answers to question 4 and 5. As shown in Appendix B, these questions address the situations where probability = 0,83 and probability = 1, respectively (for the low importance case). If the answer to question 5) was higher than the answer to question 4), then the participant was allocated to one group (which we call the 'monotonic' group); otherwise the participant was allocated to another group (the 'non-monotonic' group). As a result, 6 participants ended up in the 'monotonic' group and 9 in the 'non-monotonic' group. Plotting the results for those two groups separately yields a striking picture; see Figure 4. Although it is not surprising that the left graph is monotonic and the right graph is not (after all, we grouped the participants based on this), it is surprising that for the non-monotonic graphs, the middle part of the curve (for the cases where probability = 0,17, 0,50 and 0,83) is almost horizontal. Moreover, for the monotonic graphs, the importance of the desire does not seem to make a difference anymore. These results seem to suggest that the two different interpretations of hope mentioned above have an impact on the hope function: for people that interpret hope in the 'monotonic' way, intensity of hope is mainly determined by the probability, whereas for people that interpret hope in the 'non-monotonic' way, intensity of hope is mainly determined by the importance (except for the cases where probability = 0 or 1). Although there seems to be a clear trend in all of these effects[5], we want to stress that it is difficult to draw strong conclusions based on this pilot study with only 15 participants. Also, the current findings are heavily dependent on the assumption that people are able to verbally express their own state of hope based on introspection; hence, more research is required to confirm these findings.

[5]For example, pair-wise t-tests pointed out that the middle part of the left curve is indeed monotonic, whereas the middle part of the right curve is horizontal at the $p < 0.05$ confidence level

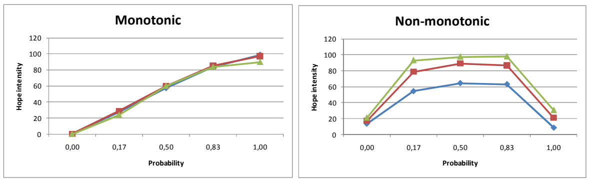

Figure 4: Different hope functions created after splitting the participants based on their answers to question 4) and 5)

3.5. Flexible hope function

The findings discussed in the previous sub-section suggest that there might not be such a thing as a 'general' hope function. Instead, the shape of the hope curve may be dependent on individual characteristics. More specifically, people may have the tendency to either express more hope in case an event is (almost) certain (yielding a monotonic hope curve) or to express more hope in case an event is highly uncertain (yielding a non-monotonic hope curve). Hence, to be able to reflect such individual difference in IVAs, it may be useful to have a hope function that features a parameter enabling the modeler to differentiate between the two types of interpretation. An example hope function that does this is shown below:

<u>Flexible Hope Function</u>

$\forall$s:state $\forall$p:probability $\forall$i:importance
expectation(s, p) $\wedge$ desire(s, i) $\wedge$ p $\leq \theta$
$\twoheadrightarrow$ hope(s, (-0.5*(cos(1/θ*π *p)) + 0.5) * i)

$\forall$s:state $\forall$p:probability $\forall$i:importance
expectation(s, p) $\wedge$ desire(s, i) $\wedge$ p > θ
$\twoheadrightarrow$ hope(s, (-0.5*(cos(1/(1-θ)*π *(1-p))) + 0.5) * i)

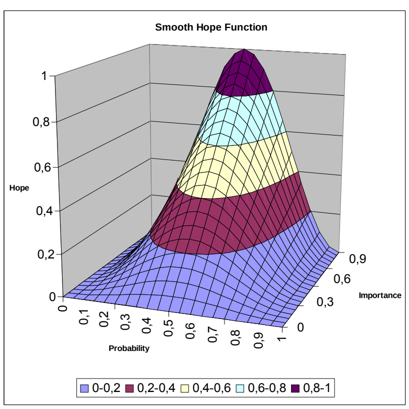

Figure 5: Hope as a function of probability and importance.

The behavior of this function for different values of probability and importance is shown in Figure 5. Here, θ is a shaping parameter (in the domain <0,1]) that can be used to manipulate the location of the top of the hope curve. The value of this parameter may differ per individual, and represents the point at which hope stops increasing monotonically (i.e., the top of the curve). This can be interpreted as the point when people stop 'putting more effort in hoping', because the outcome becomes more certain. As such, it can be thought of as some kind of 'optimism' parameter, which has been found to be a characteristic that differs per person [34]. By giving θ a value close to 1, the shape of the monotonic hope curve can be simulated. In the remainder of this paper (and also in Figure 5), the value of 0.5 is chosen for this parameter, which gives it a more non-monotonic shape.

3.6. Emotions after an event

In addition to the before-emotions, a number of prospect-based emotions are used that occur after a relevant event has taken place. In total, four types of after-emotions are considered within the presented model: *surprise*, *(dis)satisfaction*, *relief*, and *disappointment* (again, taken from [11]). These emotions usually occur when an observed world state is compared with an earlier expectation.

Let us start with *surprise*. In the presented model, agents make predictions about future states with certain probabilities. In case a state occurs of which an agent was 100% sure that it would happen, the agent will not be surprised. However, in all other cases where the state was predicted with some probability of less than 100%, the agent will experience some level of surprise. In principle, this level is proportional with the prediction failure, which is modeled in LEADSTO via the following formula:

<u>Surprise Function</u>

$\forall$s:state $\forall$p:probability
previous_expectation(s, p) $\wedge$ belief(s)
$\twoheadrightarrow$ surprise(s, 1-p)

$\forall$s:state $\forall$p:probability
previous_expectation(s, p) $\wedge$ belief(not(s))
$\twoheadrightarrow$ surprise(s, p)

Note that, for each prediction made, the model automatically generates predictions for the complement of the relevant world state. Hence, in case an agent predicts that it will be sunny with a probability of 0.3, then it will also predict that it will not be sunny with a probability of 0.7.

The next emotions addressed are *satisfaction* and *dissatisfaction*. These are based on whether a desire comes true or not, and emerge with an intensity that equals the importance of the desire:

<u>Satisfaction Function</u>

$\forall$s:state $\forall$i:importance
desire(s, i) $\wedge$ belief(s)
$\twoheadrightarrow$ satisfaction(s, i)

$\forall$s:state $\forall$i:importance
desire(s, i) $\wedge$ belief(not(s))
$\twoheadrightarrow$ dissatisfaction(not(s), i)

As an alternative, satisfaction and dissatisfaction may be modeled via different intensities of the same emotion. However, for practical purposes it was decided to keep them separated (also see the next section).

The last two emotions used in the model are *relief* and *disappointment*. Following [11], these emotions depend on the combination of surprise and (dis)satisfaction. When an agent is both very surprised and satisfied, it means that its desire has come true and the probability for this was low. In such a case, it will experience relief, a kind of happiness that an expected negative event did not come true. Likewise, one experiences disappointment when one is surprised and dissatisfied, a kind of sadness that an expected positive event did not come true. These mechanisms are modeled as follows:

Relief/Disappointment Function
∀s:state ∀i1,i2:intensity
surprise(s, i1) ∧ satisfaction(s, i2)
↠ relief(s, i1*i2)

∀s:state ∀i1,i2:intensity
surprise(s, i1) ∧ dissatisfaction(s, i2)
↠ disappointment(s, i1*i2)

Note that the relief/disappointment function makes use of the concepts surprise and satisfaction, which themselves are calculated on the basis of the concepts desire and expectation (see above). Hence, it is possible to translate the function to the following (perhaps more intuitive) form, which directly makes use of belief and desire, and is logically equivalent with the previous function:

Alternative Relief/Disappointment Function
∀s:state ∀p:probability ∀i:importance
previous_expectation(s, p) ∧ belief(s) ∧ desire(s, i)
↠ relief(s, (1-p)*i)

∀s:state ∀p:probability ∀i:importance
previous_expectation(s, p) ∧ belief(not(s)) ∧ desire(s, i)
↠ disappointment(not(s), p*i)

3.7. From emotions to actions

Different prospect-based emotions lead to different actions, depending on the context. In the context of a game, for example, an agent that hopes (and expects) to win may look confident, and behave relaxed. An agent that fears (and expects) to lose, on the other hand, may look worried, start talking in itself, or behave unfriendly towards the opponent. Thus, for a game character, a mechanism is needed that converts the emotions modeled in the previous sections into actions, depending on the context. Here, actions may include both verbal and non-verbal behavior. In order to generate these actions, the emotions may be combined with the agent's intentions (see Figure 1). The general rule to describe this mechanism is shown below. In short, this rule states that, if an agent intends to perform action a, and it experiences various emotions with intensities i1, …, i7, then it will perform a variant of the action that is shaped by the emotions (via the function f(…)):

Emotional Action Function
∀a:action ∀i1,i2,i3,i4,i5,i6,i7:intensity
intention(a) ∧ hope(i1) ∧ fear(i2) ∧ surprise(i3) ∧ satisfaction(i4) ∧ dissatisfaction(i5) ∧ relief(i6) ∧ disappointment(i7)
↠ perform(a, f(i1,…,i7))

Obviously, the function f(…) needs to be defined for a particular domain. In the next sections, an example application will be shown where a specific variant of this function is used. The idea is that each of the emotions is split up into several non-overlapping intervals (e.g., [0-0.2>; [0.2-0.4>, [0.4-0.6>, [0.6-0.8>, [0.8-1.0]). Then, if the agent intends to perform a certain action, this action is shaped according to the intervals in which its emotional states are classified. For example, an agent that is almost certain to win a dice game and is suddenly beaten by an incredibly lucky throw of the opponent (surprise ∈ [0.8-1.0]), will start shouting and look angry.

Another way in which emotional state can have an impact on agents' actions is via coping strategies. For example, agents that experience a (negative) emotional state with an undesirably high intensity could apply strategies like reappraisal or intention revision in order to decrease the intensity of this emotion. Such coping strategies are beyond the scope of the current paper, and are therefore not further addressed in the remainder of the text. However, some interesting approaches are put forward in [13, 17, 18].

4. Simulation

To test the global functioning of the presented model, it has been used to perform a number of simulation runs within the LEADSTO simulation environment [9]. The model was tested for a couple of test scenarios, as a form of 'proof-of-concept'. This section presents an example simulation run for one of these scenarios. This scenario involves an agent that inhabits a simple world consisting of four positions: p1, p2, p3 and p4, which are all connected with each other (see Figure 6). The agent starts at p1, and cannot observe the other positions from there. It has as main goal to survive, by eating food and drinking water. However, this is only present at a subset of the four positions (depicted by f and w in Figure 6). The agent has some initial expectation about where the food and water may be, but these are not necessarily correct.

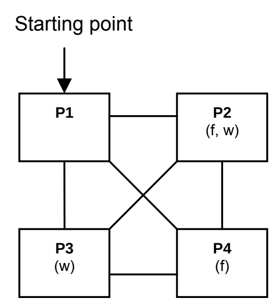

Figure 6: Example scenario.

Figure 7 shows an example of (part of) a resulting simulation trace. Time is on the horizontal axis, and different states properties are on the vertical axis. A box on top of a line indicates that a state property is true. The upper half of the figure represents qualitative information, such as the agent's desires, intentions, observations, and actions. The lower half of the figure represents quantitative information in terms of graphs that display different emotions and (on the vertical axis) their intensity.

As can be seen in Figure 7, the agent starts out (at time point 0) with two desires (namely, to be 'quenched' and to be 'stuffed'). There is food at position p2 and p4, and water at p2 and p3. However, the agent predicts that there is a low probability for food at p3, and a high probability for food at p4. It also predicts a medium probability for water at p3 and a low probability for water at p4, and predicts that there is nothing in p2. Based on these predictions, the agent first goes to p4, hoping confidently that there is food, and fearing that there is no water. This is seen in Figure 7 by the increased hope (called 'hope-cast' in the picture) for food from time point 5, as well as the intention to go to p4 at time point 5. Although the agent is confident, it is also slightly worried and therefore moves somewhat irregularly. Meanwhile, it is dissatisfied that its desire to be stuffed is not fulfilled. When the agent eventually arrives at p4 and discovers that there is food, it is satisfied and slightly relieved, but it is also dissatisfied and somewhat disappointed about there being no water. It proceeds to eat happily. After eating, its desire to be stuffed disappears and the agent is no longer satisfied or dissatisfied about the food. The agent then generates the intention to go to p3 (at time point 14). As the agent goes, it is hoping that there is water in p3, which turns out to be the case. The agent is satisfied and relieved about the water, and starts drinking happily.

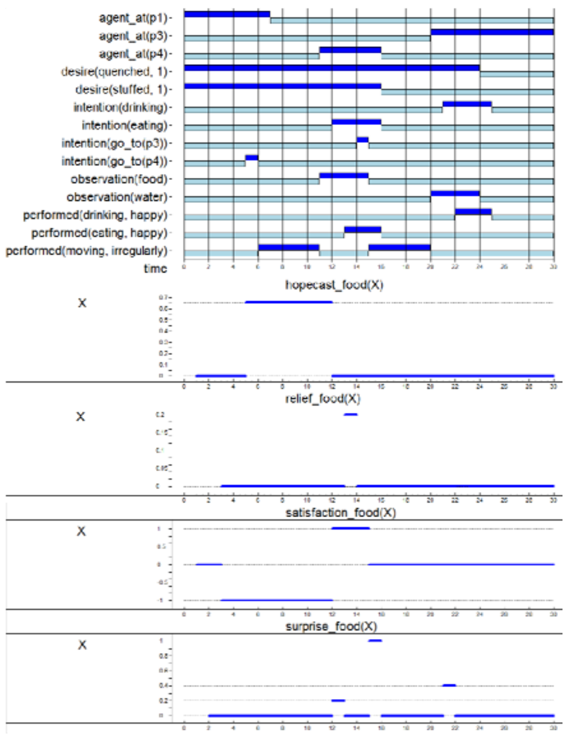

Figure 7: Example simulation trace.

After testing a number of such simulation scenarios, using different values for the parameters involved, the model was considered ready to be applied in real-world applications. These applications are described in the next section.

5. Two applications

In order to investigate the impact of the model on human beings' perceptions of game characters, two game applications have been developed. Both of these applications involve a human player and a computer opponent; they addressed the game of 'tic-tac-toe' and the dice game '2500'. The rules of both games are described in Section 5.1 and 5.2, respectively. Next, Section 5.3 describes the generic architecture that was used to implement both games

5.1. Application 1 - Tic-Tac-Toe

As a first step to test the applicability of the model, the well-known game of tic-tac-toe was implemented. Although this game would not exploit the full functionality of the prospect-based emotion model, it was selected for a first test, since it was relatively easy to implement.

The rules of the game are also rather simple. There is a 3x3 grid, the players takes alternating turns to place their own mark, either an 'x' or an 'o', on the grid. To win, a player must have three of its own marks in a horizontal, vertical or diagonal line.

The game can also be repeated multiple times. In our case, the human player would start the first game, and then the starting player is alternated with each game.

5.2. Application 2 - Dice game

The game of 2500 (a short variant of the game '5000') was selected for a couple of reasons. First, it is a dice-based game, which means that it mainly depends on *chance*, which can directly be connected to *probability*, one of the basic elements underlying the model's hope function. Second, the other basic element, *importance*, can easily be manipulated by introducing a bet that can be gained during each game. Third, the rules of the game are well defined and relatively simple, which makes it easy to implement an IVA that can play the game.

The rules of the game 2500 are as follows. Two players are involved: the human and the IVA. Each player starts with 0 points. The game consists of multiple *rounds*, in which each of the players takes one *turn*. A round is finished when each player has taken his turn. The order of the player's turns is determined at the start of the game. Whenever a player obtains 2500 points (or more), this player wins the game and receives the bet.

Each turn starts with six dice which are thrown simultaneously. A throw can deliver between 0 and 2000 points, depending on the dice that are thrown. For example, 2 ones and 1 five delivers 250 points (see [48] for the exact scoring). After a player has thrown the dice, (s)he must put aside at least one dice with points. The points of this (or these) dice are noted. If the cumulative number of points of the dice set aside is 350 or more, the player may choose to end the turn. Otherwise the player continues to throw with the dice not set aside. If all six dice are put aside, then that player's turn automatically ends. If a player does not get any points during a throw, all points of that turn are reduced to zero and the player's turn is over.

5.3. Implementation

Both the tic-tac-toe and the 2500 game have been implemented in HTML, using Javascript. Moreover, Haptek's PeoplePutty [49] has been used to visualize the IVA. This environment has been used successfully in a large variety of previous research projects (e.g., [20, 45]. It offers the ability to display faces within a script for HTML. Moods, expressions and gestures can be set for the face, as well as shapes and accessories. Furthermore, it makes use of a text-to-speech engine: text can be inputted, and speech will be given as output, with appropriate lip synching. In the current application, a number of facial expressions have been used, among which smiling, looking sad, looking happy and looking angry.

Figure 8 and 9 display a screenshot of each of the applications. In both figures, the face of the virtual opponent agent is shown on the top-left, and the state of the game on the top-right. Below that, a window is shown in which the utterances of the agent are displayed, as well as some buttons that the player can use to control the game. Furthermore, in Figure 8 a large number of additional items are shown (such as 'emotions', 'predictions', etc.) that demonstrate the internal states of the agent. During a normal game these items are disabled (e.g., as in Figure 9), but they can be useful for analysis and debugging purposes.

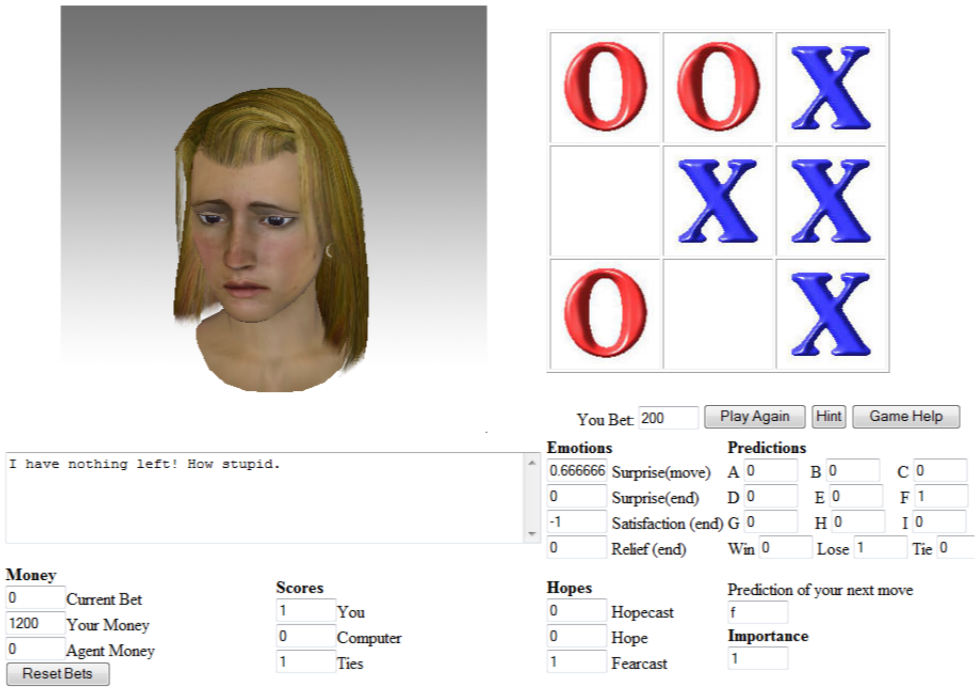

Figure 8: Screenshot of the Tic-Tac-Toe application.

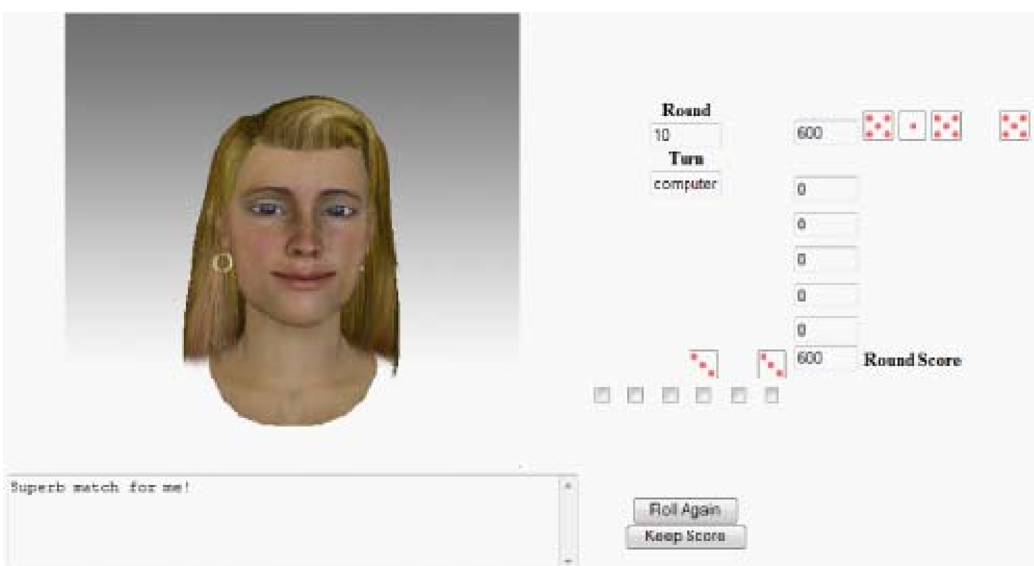

Figure 9: Screenshot of the 2500 application.

To enable the IVA to use the prospect-based emotion model for a particular game, the model has been filled with some domain-specific knowledge. For example, during each game (both for tic-tac-toe and for 2500), the agent is assigned the desire to win. Moreover, during each turn, this desire is refined to several sub-desires. During the turn of the human player, the agent desires that the human does not get any score for the turn. During its own turn, the agent desires that it does get a score.

Each time a move is made by one of the players (i.e., either a mark has been placed on the grid, or the dice are thrown, depending on the game), the agent has the intention to communicate with the user (both verbally and via facial expressions), and will thus generate an appropriate surprise, (dis)satisfaction, relief or disappointment, based on its (sub)desires and its beliefs about the game state. In the dice game, each time that one of the players sets dice aside, the agent will demonstrate hope or fear based on its desire and beliefs about the game state. Furthermore, after each turn, the agent will display hope or fear in relation to the game as a whole, and thus show its confidence that it will win, its worry about not winning or fear that the human player wins.

To convert emotional states to actual behavior, two of the mechanisms mentioned above are exploited: facial expressions and emotional utterances. To generate facial expressions, the states in the model can directly be mapped to parameter settings in PeoplePutty. For example, if the IVA has a satisfaction of 0.7, this is visualized by setting the slide bar for "happy" provided by the software to 70%. To generate emotional utterances, a database of domain-specific utterances has been created. To fill this database, following Section 3.7, each of the emotional states has been split up into some non-overlapping intervals, and for each interval, a number of utterances have been specified. For example, if surprise<0.2, the agent chooses among several statements like: "`Not a surprising roll`", "`I saw that roll coming`", and "`I knew that one would come up`". Also multiple simultaneously occurring emotions (e.g., hope and satisfaction) may lead to certain utterances. The advantage of this approach is that one does not have to define statements for each possible situation in the game, since these situations are classified in terms of high level emotional states of the IVA.

As mentioned earlier, all emotions are generated based on *importance* and *probability*. The importance is also dynamic. For example, it is more important to get points if the opponent is close to winning (e.g., for the dice game, if the opponent has almost 2500 points). It is less important to get points if the opponent is far from winning, thus in the opening phase of the game. In addition, this importance depends on the overall bet of the game.

The strategy of the agent within both games was relatively simple. For the tic-tac-toe game, the code of an existing online tic-tac-toe program[6] was re-used, and the desires were set in such a way that this code is followed. The probabilities of moves made by the opponent are based on the expectation that the opponent will use the same strategy as the agent itself. For the dice game, in each round, the sub-desire of the agent is 'getting 350 points or more'. This will always result in the intention to put aside all dice that deliver points, and keep rolling until the agent has reached 350 points or more, independent of the overall game status. In order to calculate probabilities of throws, the agent makes estimations of the actual probabilities, using ordinary statistics.

The dice game can be played at the URL in [48] (note that some software needs to be installed, and that the operating system's own standard voice is used).

6. Experiment

To evaluate how humans perceive the developed game character (with our model for prospect-based emotion elicitation), the following experimental setup has been used. Four variants of the '2500' application have been developed, with different implementations of the IVA:

1. The IVA uses no emotion elicitation model at all.
2. The IVA uses the complete emotion elicitation model.
3. The IVA uses a variant of the model with opposite, incongruous emotions. For example, the IVA is happy where it is supposed to be sad.
4. The IVA uses the complete model, but only the 'after-emotions'. All 'before-emotions' have been omitted.

Here, variant 1 serves as the control condition. Variant 3 has been added to test whether it makes a difference if the emotions displayed by the agent are consistent with the current situation or not. The decision to include this incongruous variant was inspired by [27], in which this approach is motivated by the finding that 'the agent's expressions of emotions may be harmful to the interaction when they are incongruous to the situation'. Variant 4 is another control condition, to compare the impact of 'before-emotions' (i.e., hope and fear, see Section 3) with the impact of 'after-emotions' (i.e., surprise, (dis)satisfaction, relief, disappointment). In variant 2, 3, and 4, all emotions are shown both via facial expressions and utterances.

Twenty-four people participated in the experiment. The age of the participants ranged between 60 and 18, with a mean age of 28.3 and a standard deviation of 13.1. Among the participants, 19 were male and 5 were female. For each participant, the experiment lasted between 30 to 45 minutes, depending on their skills and their luck in each of the games.

Before starting the experiment, the participants were told the agent's name was "Anna". The rules of the game were explained to them and they were allowed to play a single test round with variant 1, the neutral agent, to get familiar with the rules. After this, the participants played one game with each variant of the application, i.e., they played the game four times. Since there are four variants, there were 24 possible orderings. These orderings have been distributed randomly among the 24 participants.

In each of the plays, the money at stake was set to a maximum. This means that all plays were maximally important for both the agent and the human player. After each game, the participants had to fill in a questionnaire, asking them to award a measure of agreement of a number of statements regarding that particular agent. These statements were distinguished in two categories: the first category

[6] See http://www.calculatorcat.com/games/tic_tac_toe.phtml.

addressed the user's perception of the behavior and believability of the IVA, whereas the second category addressed the perceived game play (see next section). A gradual seven-point scale was used, with the following meaning: 1='I strongly disagree', 2='I disagree', 3='I weakly disagree', 4='neutral', 5='I weakly agree', 6='I agree', 7='I strongly agree'.

7. Results

To analyze the results of the experiment, one-way between subjects ANOVAs have been applied on the answers to the statements of the questionnaire, using the variant of the IVA as independent variable and the participants' rating as dependent variable. Section 7.1 describes the results for the statements related to the perceived behavior and believability of the IVA, and Section 7.2 for the statements related to game play.

7.1. Perceived behavior and believability

The statements addressing the perceived behavior and believability of the IVA were the following:

- "Anna was believable"
- "The behavior of Anna was human-like"
- "I thought Anna's reactions were natural"
- "Anna reacted on my actions"
- "Anna was interested in the game"
- "Anna did not care about the game situation"
- "Anna wanted to win the game"

There were four variants: the non-emotional (NE) variant, the full emotional variant (FE), the incongruent emotional (IE) variant and the emotional variant without 'before-emotions' (E). The results are presented in Figure 10 and Table 2. The vertical axis in Figure 10 corresponds to the scale explained in Section 6. The error bars represent standard deviations. In Table 2, the first column indicates the statement, and the rest of the columns indicate pair-wise comparisons between different variants. The 'overall' column shows whether there was a general significant effect over all variants for that statement (which was determined by performing a single ANOVA on all four variants). The cells show whether the comparison yielded a significant result or not. Here, 'n.s.' means 'not significant', '*' indicates $p < 0.05$, '**' means $p < 0.01$, and '***' stands for $p < 0.001$.

Additionally, post hoc pair-wise comparisons were performed using the Tukey's HSD test. The results of these comparisons are shown in Table 2 between round brackets. Again, we use the notation 'n.s.' for 'not significant', '*' for $p < 0.05$, '**' for $p < 0.01$, and '***' for $p < 0.001$.

As an example, consider the second cell of the fifth row, which states 'FE***' and '(**)'. This means that, the full emotional variant was found to be rated as significantly more interested in the game than the non-emotional variant, both according to the ANOVA (on the $p < 0.001$ level) and according to the Tukey's HSD test (on the $p < 0.01$ level).

These results clearly show that the non-emotional variant was perceived worst with respect to all aspects related to believability, followed by the incongruent variant. This confirms our hypothesis that adding prospect-based emotions in an incongruous manner does not enhance believability very much. The scores of the two remaining variants are significantly higher than those of the other two. Among these two variants, the full emotional variant is perceived to react better on actions, to be more interested and to care more about the game play. However, its general believability, human-likeness, ability to provide natural reactions, and desire to win are not considered to be significantly greater compared to the emotional variant without 'before emotions'.

In general, these results are encouraging, since they confirm the ability of the model to enhance believability. However, to explain the small differences between the two emotional variants, it is needed to take a closer look at the experiment and the results.

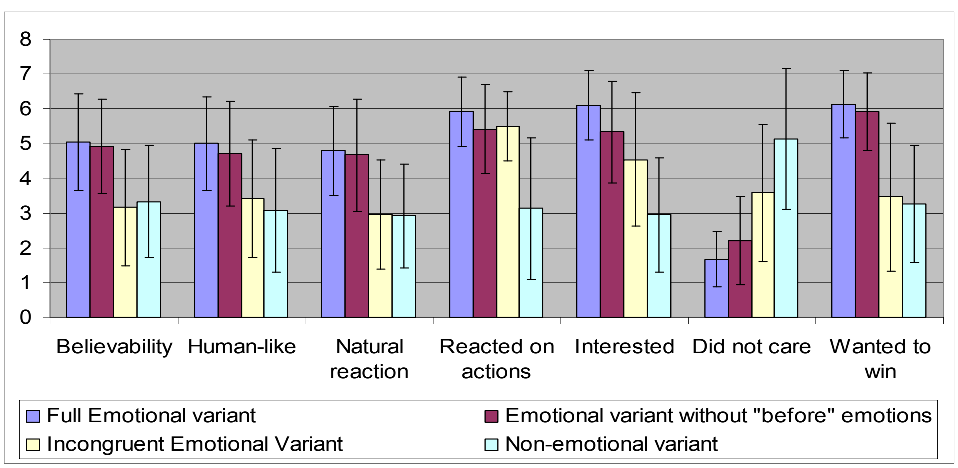

Figure 10: Statistical results of the experiment - perceived behavior and believability of the IVA.

Table 2: Detailed statistical results - perceived behavior and believability of the IVA.

Statement	FE-NE	FE-IE	FE-E	NE-IE	NE-E	IE-E	Overall
Believability	FE*** (***)	FE*** (***)	n.s. (n.s.)	n.s. (n.s.)	E*** (***)	E*** (***)	***
Human-like	FE*** (***)	FE*** (***)	n.s. (n.s.)	n.s. (n.s.)	E*** (***)	E*** (**)	***
Natural reaction	FE*** (***)	FE*** (***)	n.s. (n.s.)	n.s. (n.s.)	E*** (***)	E*** (***)	***
Reacted on actions	FE*** (***)	FE* (n.s.)	FE** (n.s.)	IE*** (***)	E*** (***)	n.s. (n.s.)	***
Interested	FE*** (***)	FE*** (**)	FE** (n.s.)	IE*** (***)	E*** (***)	E** (n.s.)	***
Did not care	NE*** (***)	IE*** (***)	E** (n.s.)	NE*** (**)	NE*** (***)	IE*** (**)	***
Wanted to win	FE*** (***)	FE*** (***)	n.s. (n.s.)	n.s. (n.s.)	E*** (***)	E*** (***)	***

Within this application, the ‘before emotions’ were expressed in terms of statements about the events in the near future (e.g., “`Please, dice, points for me!`” or “`I fear this will get worse for me!`”), whereas the ‘after emotions’ were about events in the recent past (e.g., “`YES! Points for me!`” and “`How did this happen? Stupid dice!`”). Apparently, having only the latter was already sufficient to make the agent significantly more believable and human-like. The addition of the ‘before emotions’ did not make much difference for this. However, the presence of the ‘before emotions’ did provide Anna the appearance of being more interested and involved in the game. Although these results should not be over-generalized, it is an indication that ‘before emotions’ like hope and fear enhance the perception of involvement in a situation. Especially for IVAs in games, this is a nice feature, since people generally prefer playing against opponents that care about the game. In future work, the role of ‘before emotions’ will be studied in more detail.

7.2. Perceived game play

In addition to the perceived believability of the game character, we investigated how the availability of (prospect-based) emotions affected the experienced game play of the users. It is important to realize that this a different type of research question. Although it seems plausible that believable game characters enhance the fun when playing the game, this is not a trivial conclusion. The statements addressing the perceived game play were the following:

- “Anna played a strong game”
- “I liked playing the game with Anna”
- “Anna’s presence added something positive to the game play”
- “I disliked the game ‘2500’”

Again, the four variants NE, FE, IE and E were used. The results for these questions are presented in Figure 11 (again, the error bars represent standard deviations) and Table 3 (again, based on one-way between subjects ANOVAs and post hoc pair-wise comparisons via the Tukey’s HSD test).

As shown by these results, the question whether Anna played a strong game or not seemed to be largely unrelated to the variant played, although the incongruent variant was perceived to play a somewhat stronger game. However, the agent’s strategy was constant across all variants. The used strategy itself was not perceived to be leading to a particularly strong game, since the average result was a neutral opinion.

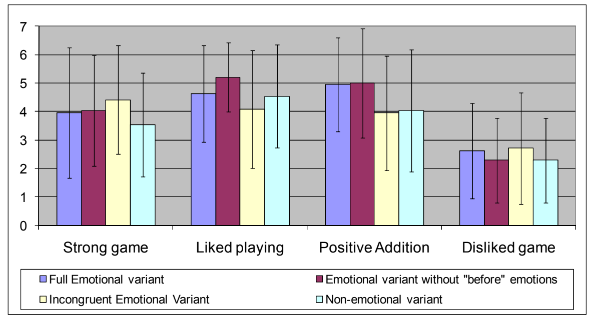

Figure 11: Statistical results of the experiment - perceived game play.

The participants liked playing more with the emotional variant without “before” emotions compared to the other variants, which on average scored more towards a neutral opinion. Similarly, whether Anna’s presence was a positive addition to the game play or not resulted in an on average neutral opinion for to the non-emotional and incongruent emotional variant. The emotional variants were considered a more positive addition to the game play. While the emotional variants were perceived as significantly more positive to the game play, there was no significant effect on whether the game was disliked more or less for those variants. This matches the intent, for the statement was intended to represent whether the participant liked the game *itself*, independent from the presence of Anna. Also, the game itself was not disliked a lot, as the average is a mild disagree with the statement “I disliked the game ‘2500’”, as seen in Figure 11.

In general, we can conclude that the emotional variants are considered a positive addition to the game play, while the opinion is neutral about whether the non-emotional and incongruent variants are a positive addition.

Table 3: Detailed statistical results - perceived game play.

Statement	FE-NE	FE-IE	FE-E	NE-IE	NE-E	IE-E	Overall
Strong game	n.s. (n.s.)	n.s. (n.s.)	n.s. (n.s.)	IE* (n.s.)	n.s. (n.s.)	n.s. (n.s.)	n.s.
Liked playing	n.s. (n.s.)	n.s. (n.s.)	E* (n.s.)	n.s. (n.s.)	E* (n.s.)	E*** (*)	*
Positive addition	FE** (n.s.)	FE** (*)	n.s. (n.s.)	n.s. (n.s.)	E** (*)	E*** (*)	**
Disliked game	n.s. (n.s.)	n.s. (n.s.)	n.s. (n.s.)	n.s. (n.s.)	n.s. (n.s.)	n.s. (n.s.)	n.s. (n.s.)

An interesting finding is that the full emotional variant does not seem to have an added value (at least, with respect to game play) over the variant without 'before' emotions. A possible explanation for this finding is the fact that the users perceived the agent with the full emotional model as a bit unfriendly at times. For instance, having emotions like hope and fear often caused the agent to say things like "`I really hope you will not have any points this time`". In follow-up studies, it might be interesting to explore how users perceive an agent that has the full emotional model, but that shares some goals with the human player (e.g., as some kind of personal coach). It is not unlikely that people will like to hear such an agent express its hopes and fears more often.

8. Discussion

Computational models of emotion exist in many flavors these days. However, empirical studies that evaluate the impact that such models have on virtual game characters are scarce. As a result, there are still a number of open questions regarding how human players perceive emotional game characters. The main contribution of the current research was to provide some answers to these questions, in particular when it comes to game characters with prospect-based emotions.

To this end, an executable model for prospect-based emotions was introduced, and used within an evaluative study in the context of a dice game. The model was defined in such a way that it is generic, easy to use, and representative for some of the influential emotion models in the literature. In particular, the model was inspired by [11] and [17, 18]. Since a conceptual distinction has been made between the generic and domain-specific parts of the model, it is relatively easy to plug it in within game characters in different applications. In fact, the only thing that needs to be done is filling in some slots with domain-specific knowledge (such as the utterances mentioned in Section 5.3). The model has been implemented and tested (via proof-of-concept simulations) using the modeling language LEADSTO. In addition, two game applications have been developed, in which a human can play games against an IVA that is equipped with the model.

The evaluative user study, which has been performed for the dice application, indicated that the model significantly enhances the agent's believability, especially when it comes to its involvement in the situation. This is an encouraging finding, since people generally prefer playing games against opponents that care about the game. With respect to the participants' perceived game play, the emotion model also turned out to be beneficial, although no added value was found for the 'before' emotions compared to the other emotions. We speculate that this is caused by the fact that the agent with the full emotional model was sometimes perceived as being a bit unfriendly.

The global trend of these findings is consistent with results reported in the literature, in which several comparable studies are reported with the aim to evaluate believability of (prospect-based) emotion models in game context. For example, from their evaluation of "iCat, the Affective Chess Player", Pereira et al. conclude that 'The use of anticipatory mechanisms increases character's believability, allowing for a more engaging experience for the user. This factor positively affects the likeability of the character, increasing user's attention to the game and motivation to interact with iCat' [32]. Similarly, Martinho and Paiva evaluate believability of an affective agent in the context of a puzzle game. They evaluate the following aspects: the smoothness of the animation, the naturalness of the behavior, the level of expectation of the subject regarding the provided behavior, the similarity with the behavior of a person in the same situation, the ease of understanding the displayed attention and emotion, and the general impression left by the synthetic character. They formulate the following conclusion: 'Believability seems to be influenced by all evaluated aspects of the experience except for the smoothness of the animation.
It is congruent with the fact that more complex animation does not necessarily means more believable. Our results confirm that both the focus of attention and emotional state play a more important role in the definition of believability' [25]. In another study, Becker-Asano and Wachsmuth evaluated the believability of the emotion-endowed virtual human MAX in the context of the card game Skip-Bo. In their emotion model, they distinguish between 'primary emotions' (i.e., basic response tendencies) and 'secondary emotions' (such as 'relief' or 'hope'). They report the interesting finding that 'MAX with primary and secondary emotions "in concert" was judged significantly older than MAX with simulated primary emotions alone' [4]. Furthermore, a number of studies formulate global conclusions about the impact of incorporating emotion models in game characters on perceived believability. For instance, in an evaluation of affective poker playing agents, Gebhard et al. state that 'Especially the continuous computation of short-term emotions and medium-term moods allow for a smooth blending of different aspects of affective behavior that help to increase the believability and the expressiveness of virtual characters' [15]. And in an evaluation of emotional virtual soccer players, Bosse and Höhle conclude that 'the participants very much appreciated the players' abilities to show emotions and trust. Overall, they had the idea that the presented model made the agents more believable, and that it enhanced the experienced fun when watching the soccer games' [7].

Despite the encouraging results, our findings should be interpreted with some care. In particular, one should be aware that the results depend on the assumption that participants are capable of verbally reporting their own state (via post-hoc questionnaires) in an adequate manner. A complementary approach would be to apply modern emotion recognition techniques (such as facial tracking [2, 41]) to assess the user's mental state at runtime. Also, the added value of the non-monotonic hope function could be evaluated more thoroughly, for instance based on the approach used in [19].

Furthermore, to explore some of the above issues in more detail, in follow-up research it is planned to incorporate the presented model within a teammate agent instead of an opponent agent. The experiments performed so far only addressed situations in which the emotional IVA had goals that were opposite to the goals of the user. It may be expected that the perception of an IVA using our model will differ when the human is playing with (instead of against) the IVA. Having more insight into the difference between these two cases will provide game designers even more insight into the behavior that human players want to see in computer game characters, thereby bringing game play experience one step further.

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