Building Emotional Agents for Strategic Decision Making

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Abstract: Experimental economics has many works that demonstrate the influence of emotions and affective issues on the process of human strategic decision making. Personality, emotions and mood produce biases on what would be considered the strategic solution (Nash equilibrium) to many games. Thus considering these issues on simulations of human behavior may produce results more aligned with real situations. We think that computational agents are a suitable technology to simulate such phenomena. We propose to use O3A, an Open Affective Agent Architecture to model rational and affective agents, in order to perform simulations where agents must take decisions as close as possible to humans. The approach evaluation is performed trough the classical 'prisoner dilemma' and 'trust' games.

1 INTRODUCTION

There is enough evidence about the behavioral issues of the decision-making process (Lerner et al., 2004; Elbanna, 2006; Seo et al., 2010). Phenomena like the individual "risk aversion" (how tolerant is an individual to risk) (Loewenstein et al., 2001), or the "illusion of control" (overestimation of individuals of their ability to control events) (Schwenk, 1984), also involve the affect of the decision-maker. Thus, for example, an owner of a property that has benefited from it for many years, and has affective bonds with it, would try to sell the property at a higher price than an investor that has not relation with the property. Bearing all this in mind one may assume that when performing experiments with human that must make strategic decisions, it is very likely to get individual biased action profiles regarding to what should be a rational solution. Therefore, when simulating human behavior in scenarios of strategic decision-making, the representation of the individual affect may become an important parameter in order to get results better aligned with a real situation. Computational agents could be a suitable technology for creating such simulations. This field has evolved enough to build rational entities with a human-like practical reasoning (Weiss, 1999). The BDI architecture is a widely accepted conceptualization for agents that includes on its definition representative elements of human characteristics. Nevertheless one of the biggest challenges in this area is to provide the agents with the necessary structures in order to reach an accurate representation of the human affective side. Some steps have been taken inspired on psychological and/or neurological grounds (Marsella and Gratch, 2009; Becker-Asano and Wachsmuth, 2010), nevertheless a bigger effort must be done to offer less disperse approaches and to follow an incremental line of research (Marsella et al., 2010).

With this work we want to address some important questions: is it possible to build a scenario with entities representing humans that can take decisions as humans do? How can an affective component bias results from the rationally optimal solution? How to model this to properly simulate the strategic decision-making process in humans? We want to give an answer to these and other questions. Our aim is to model entities able to behave as humans do by integrating rational and emotional components, and offer them as what-if tools than can behave as and interact with human in situations of strategic decision making. We propose an instantiation of the Open Affective Agents' Architecture. Our approach is grounded on strong psychological and neurological fundaments.

In order to validate our proposal we have implemented it, and we have used classical games of experimental economy (as the prisoner's dilemma, dictator, ultimatum and trust games). This what-if tool allows to tune human affective characteristics in multi-agent systems and analyze how they influence the decision-making process in classical games.

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The rest of the paper is organized as follows. A review of the related literature is presented in section 2. The main components of the supporting architecture of the approach are described in section 3. Assumptions, considerations as well as the main architecture components are described in section 4. In section 5 the experiments performed as well as their results are offered. Finally, section 6 offers a discussion and the conclusions of the work.

2 RELATED WORK

2.1 Psychological and Neurological Background

Psychology uses various concepts to describe the affective characteristics of humans. At first there are individual intrinsic traits that influence motivations and behavior known as *personality* (Ryckman, 2007). Then we found approaches about *emotions* whose definitions vary depending on researchers and disciplines, but researchers generally agree on the notion of reactions as a consequence of events, actions of other agents, and/or objects (Ortony et al., 1988). Another issue considered in psychological literature is that, regardless of the emotions experienced after an event, humans keep a kind of temperament or *mood*, which has less intensity than emotions, is also an experiential component but lasts longer and is not necessarily associated to a cause (Mehrabian, 1997). Personality and emotions have been addressed from different perspectives by important psychologists and scientists (Cornelius, 2000; Ryckman, 2007). The cognitive perspective stands out among the others for computational applications. On the other hand neurological experiments use advanced technology to find out the way the brain works on linking the human emotions mechanism and cognition processes (Pessoa, 2008). A. Damásio and J. E. Ledoux works have been very relevant on the study of the emotions and the brain (LeDoux, 1998; Damásio, 1994). Damásio argued that in some situations affective factors, as powerful heuristics of the brain to solve complex problems, may get better decisions than rational factors (Bechara et al., 1997), in that they alleviate individuals of the overloads that may come by using only cognitive processes when facing complex choices.

2.2 Computational Approaches

In this section we review some approaches that address the main processes related to the affective side of individuals from a cognitive perspective. These processes include the appraisal, the affect internal dynamics and the affect consequences. The way they dial with the different processes as well as the main psychological concepts related to affect is often partial and domain specific. There are interdisciplinary approaches that are continuously used (Ortony et al., 1988; Mehrabian and Russell, 1974; Ekman, 1999b). They have become widely accepted alternatives due to their suitability for computational applications.

The BDI architecture has commonly been a starting point to model rational agents. This is the case of (Jiang et al., 2007). The authors propose a practical reasoning separated from the emotions mechanism, and primary (infant-like emotions such as “angry”, “happy” or “surprised”) as well as secondary emotions (prospect-based and directly related to expectations and past experiences) receive a differentiated attention when they influence the process of decision-making of a traditional BDI architecture. The emotional state of the agent is represented through a set of emotion intensities. This state influences the way beliefs are acquired from communication or contemplation and also the prioritization of the agents desires. All emotions, beliefs, desires and intentions are assigned a priority. Emotions prioritize desires and they also help to decide intentions. In this architecture individual differences associated to emotions are determined by the specific model used on each agent to deal with emotions. The dynamic change of the affective state is not considered and there is no feedback from previous situation that allows to learn from emotional states.

S. C. Marsella and J. Gratch created EMA, which stands for “EMotion and Adaption” (Marsella and Gratch, 2009). They describe a computational model for the dynamic of emotional appraisal, and provide a framework based on a domain independent architecture for emotional agents. In EMA a computational model of appraisal uses the interpretation of a person-environment relationship (causal interpretation), and this interpretation is done in terms of a set of appraised variables and is altered by a set of “coping strategies” (processes that manipulate this representation to respond to the appraised interpretation). The appraised variables have some values for each proposition extracted from the environment which are stored in the *Appraisal frames*. These variables are: relevance, perspective, desirability, likelihood, expectedness, causal attribution, controllability and changeability. A two-level notion of emotional state is modeled: appraisal and mood. The first determines the agent coping response, and the second has an indirect effect on appraisal in that it is applied a mood adjustment to individual *appraisal frames*. Symbolic labels of emotions (like fear, joy or hope) are assigned to appraisal frames, but the agent coping responses are determined by the appraisal variables. Mood is represented through a set of emotion labels with some intensity. Again in this approach individual differences are not clearly modeled and the emotions component cannot be easily detached from the practical reasoning of the agent to allow its improvement or modification.

C. Becker-Asano and I. Wachsmuth built WASABI (Becker-Asano and Wachsmuth, 2010). WASABI is an architecture for affect simulation whose model of core affect is based on the PAD theory (Mehrabian, 1997), and its appraisal process is inspired by Scherer's sequential-checking theory (Scherer, 2001). This model distinguishes primary and secondary emotions. It is based on (Damásio, 1994), (LeDoux, 1998), (Ekman, 1999a) and (Ortony et al., 2005) theories. Mood is modeled as a background state whose value moves in a bipolar scale of positive versus negative. Other issues added to this proposal are the memory and emotion dynamics components. This work was used for simulating emotions capabilities in a virtual player. The significance of primary and secondary emotions was evaluated. Specific structures for dealing with each virtual character personality and individual traits are not explicitly defined in the architecture. Its range of domain applications moves around virtual characters and robotics, since it has embedded elements for physical behavior like facial expressions as manifestation of emotions. Nevertheless in order to achieve complex cognitive behaviors its integration in other domains like multi-agent simulations is difficult.

R. Santos *et al.* describe a group decision-support system that combines personality, emotion and mood. The approach is based on the Five Factor Model (FFM) to represent the personality (McCrae and John, 1992), and the PAD space to model mood (Mehrabian, 1996b). The emotional system uses the Ortony's improved version of the OCC model of emotions (Ortony, 2003). Emotions then influence the argumentation process after being mapped to the PAD space (following (Gebhard, 2005)), and also personality is considered in the argumentation phase. Although many affective concepts are considered in this architecture it is specific for a scenario of negotiation with argumentation in a group and it is difficult to separate the overall practical reasoning of the agent.

A. Fagundes *et al.* develop an architecture for emotional agents. Again the affective components emotions, personality and mood are integrated in a BDI architecture. The results of the ALMA project (Gebhard, 2005) are used, and hence the OCC, PAD and the FFM theories. Although the focus of the approach is on the cognitive state and it is easy to be applied to various situations, it makes strong assumptions such as the "discarding" of percepts or elements of the memory if they don't rise intense emotional states or if they don't lead to a desirable emotional state. Also there is not a possibility for adapting the way emotions and mood influence the cognitive processes for particular requirements.

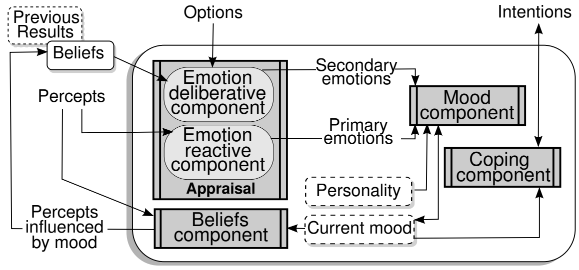

Figure 1: Main components of the O3A architecture.

In (Alfonso et al., 2014) we propose "O3A" (an Open Affective Agent Architecture). It mainly pursues to be open enough to allow different implementations of its components in order to be adapted to different situations. It also integrates the most important concepts addressed on psychological theories about affect and emotions on humans in a BDI architecture. This way the practical reasoning and affective issues converge in a single representation where the responsibilities of each component are well defined and interact to produce diverse, adaptive, and believable behaviors on agents. It will be better described in section 3.

3 SUPPORTING ARCHITECTURE

Based on the appraisal theory, O3A combines mental, cognitive and motivational issues with an affective component (Alfonso et al., 2014). O3A is build over a BDI architecture, what allows it to reuse all the machinery of the widely accepted BDI structure. Moreover O3A brings some of the most important and accepted theories in psychology and neurology related to emotions.

3.1 Main Components

The O3A basic structure is depicted in figure 1. Four main components are in charge of regulating the emotional processes: appraisal, emotions dynamics, and the influence of emotions on beliefs and on intentions.

Appraisal Component. Controls how emotions are derived from the environment and also from the current agent state. This task is performed by two subcomponents: the *emotion reactive component* and the *emotion deliberative component*. The former derives primary emotions, which follows the idea of "onto-genetically earlier emotions" (Becker-Asano and Wachsmuth, 2010) like those experienced by an infant. The later determines secondary emotions considering that they are the result of more complex chains of reasoning.

Beliefs Component. Depending on the agent current mood, percepts may trigger different effects. The judging of the value and importance of objects and events is influenced by the affective valence and arousal; for example the likelihood of seeing a potential trait increases when experiencing fear (Zadra and Clore, 2011).

Mood Component. It is in charge of deriving a global temperament or mood on the basis of the perceived emotions and the previous mood. Personality determines which is the mood of the agent when it is in a neutral or "equilibrium" state. This component also controls the way mood returns to this "equilibrium" state.

Coping Component. It has a close relation with the agent intentions since it determines how the current mood finally influences the selection of the next action to perform through the prioritization of its intentions.

4 COMPONENTS DESIGN AND CONSIDERATIONS

4.1 Components Design

O3A is open on its definition which allows to use different theories in order to determine how each one of its processes must be performed. Hence, for characterizing the way in which some of the architecture components specifically works, we were inspired by previous works that fit to each component definition, and simultaneously we offer our own vision of the not covered issues. The main theories used to instantiate the O3A Components are based on the works of (Ortony et al., 1988), (Mehrabian, 1996b) and (Marsella and Gratch, 2009). These works have proven to produce relevant results in the area and are versatile enough to be reused in new approaches.

In our design the *emotion reactive component* assumes that percepts are labeled with the "more common emotions" to be experienced given these percept. So for example the percept "hurricane" may have an associated "fear" label that becomes the corresponding primary emotion after been processed by the emotion reactive component. The *emotion deliberative component*, as stated on its own definition, performs a more complex processing and considers more factors in order to derive secondary emotions. In our design secondary emotions are derived from events of any nature. They can be internal events (like the beginning of a new intention) or external (a percept). Events are characterized according to five variables: desirability, likelihood, expectedness, causal attribution, and controllability. The definition of each one of these characteristics is similar to the variables of the appraisal frames presented in (Marsella and Gratch, 2009). From this work it was also used the mapping from the appraisal pattern to emotion labels, which are secondary emotions in our design. The variables characterizing the appraisal frames are linked to the agent mental state and they are:

desirability: linked to the agent general standards or preferences of the event consequences. For example if an agent is given a possibility to play in one of two lotteries and the minimum to pay in both is higher that the prize, the desirability of the event "time to play" will be very low. On the other hand, even if the prize is lower, but the collected money goes to charity, and it is significant for the agent, the desirability will be high. We have called this property "personal benefit", and is applicable to each possible option to carry out the intention triggered by the event.

likelihood: this variable is linked to the likelihood of outcomes. It considers the existence of past or future states. Currently our implementation of the *emotion deliberative component* only considers present propositions so the value for this variable is always 1.

expectedness: linked to the agent expectations associated to the event. Whether the expectations are fulfilled or violated may produce emotive reactions and hence changes in the agent mood.

causal attribution: whether the event was produced by the agent or by other agent or source.

controllability: linked to the capacity of the agent to react in some way to the event. If there are no actions defined to respond to the event its controllability will be low.

On the other hand, the *Mood* component is in charge of keeping the "current mood" updated. We used the PAD dimensional approach (Mehrabian and Russell, 1974) for representing the mood. The initial mood is defined by the agent personality (it is specified in the agent definition). For representing the personality we used the Five Factor Model (McCrae and John, 1992). The FFM is able to accurately describe individual traits through five dimensions (openness, conscientiousness, extraversion, agreeableness, and neuroticism). The current mood will be updated as soon as the emotions are appraised in such a way that with a positive mood, the agent is less likely to experience a negative mood and vice versa. In particular the mapping from the agent five dimensions of personality to the three dimensions of the PAD space to establish the initial mood is done according to Mehrabian's work (Mehrabian, 1996a). On the other hand, the transformation of the set of emotions appraised into the PAD mood follows the result of P. Gebhard in (Gebhard, 2005). The *Coping* component then feeds on the current mood in order to establish a priority for the agent intentions. This requires to represent a proper measure for each intention indicating benefits, risks and other factors that may be biased by the agent current mood. Currently we limit this measure to the intention risk, that is, a measure of possible losses or undesirable states for the agent, having in mind the widely treated issue of risk aversion in the behavioral economic literature (Loewenstein et al., 2001; Harrison and Rutström, 2008; Demaree et al., 2009). In particular some works demonstrate that the influence of the trait Dominance of the PAD space is a significant indicator of the risk of the decision (Demaree et al., 2009).

5 EXPERIMENTS AND RESULTS

5.1 General Design and Integration in Jason

We have used the BDI algorithm of Jason (Bordini et al., 2007) to integrate the O3A emotional components in a BDI architecture. This algorithm offers all the necessary elements to carry out the proposed design. Table 1 shows the main elements of the model and how they are inserted in the Jason inner structure. Current mood, and primary and secondary emotions are modeled as internal objects of the Jason architecture. The agent personality is specified in the agent definition and it is stored on its corresponding internal structure. On the other hand, to perform an intention, each plan must have a set of necessary "personal benefit arguments" in order to evaluate the "benefits" of each possible option of the agent according to its preferences and standards. The "associated risk" is in line with the global preferability of each possible option. The process of derivation of the primary emotions uses perceptions from the 'Perceive' process of Jason. Secondary emotions are determined through the *GET-SECONDARY-EM* process and takes the event to be processed on each reasoning cycle deriving, if it is appropriate, the secondary emotions. This process feeds on *Beliefs* and on the *Desires* derived in the Jason 'Get_option' process. The initial mood is set on the process of agent initialization and the current mood is updated each time new emotions are appraised. After selecting an event to process, the possible options for an agent are the Jason "applicable plans". Then the Jason 'Filter' process is customized in order to consider also the agent current mood.

Table 1: Integration of the affective components in the Jason platform.

VARIABLES	
Description	**Jason element**
Current Mood (M)	Internal Object
Primary Emotions (PEm)	Internal Object
Secondary Emotions (SEm)	Internal Object
Personality (P)	Agent definition
Plans attributes	
Associated risk	Plan annotation
Personal Benefit args.	Agent rule
PROCESSES	
Description	**BDI integration**
GET-PRIMARY-EM *input*: Labeled perc. | *output: PEm*	Perceive
GET-SECONDARY-EM *input*: Events | *output: SEm*	Get_option *Beliefs*
SET-INITIAL-MOOD	Initialization
UPDATE-MOOD	
FILTER-APPLICABLE-PLANS	Filter

5.2 Two Classical Games and Results

Strategic games are an important tool in experimental economy to evaluate how individuals behave in situations where a single decision must be taken (Swope et al., 2008). In many of these games there are generally two players involved, and there is also a stable equilibrium concept called "Nash equilibrium": situation where no player can obtain more benefits by taking a different decision. Nevertheless, what happens in real situations is that individuals take decisions biased by emotions. Our proposal aims to model the behavior of individuals in real situations where decisions are taken considering rational and emotional aspects. We have chosen the *Prisoner dilemma* and the *Trust Game* in order to evaluate if the decisions influenced by emotions in our system are similar to the decisions of individuals in a real context.

Prisoner Dilemma (PD)

This game offers a model of cooperation that emphasizes how individual and collective interests coexist

(Axelrod and Hamilton, 1981). The participants represent two prisoners. Each one has the opportunity to declare that the other committed the crime and hence to **betray** him, or otherwise **cooperate** with him and remain silent. For each possible situation the consequences are (Tucker, 1983): i) both prisoners betray the other: 2 years in prison for both, ii) prisoner 1 betrays prisoner 2 and prisoner 2 remains silent: prisoner 1 gets free and prisoner 2 gets 3 years of prison, iii) both prisoners remain silent (cooperate): both get 1 year of prison. The most rational option according to economic theory would be that they both betray each other (Sewell, 2010), nevertheless a systematic behavior in humans is to have a silent participant side what is an evidence of cooperation between them.

The code of figure 2 is an extract of the *agentA* implementation. It expects that *agentB* is not going to betray (line 1). The expectation is represented through a rule with an “EventFunctor” (the event that triggers the expectation verification), a fulfillment condition (that belief that makes the expectation to become fulfilled) and a violation condition (a belief that is the opposite of the fulfillment belief)[1]. The personal benefit of the agent for each option is determined trough the rule of line 2. The agent basically looks for an option that reports to him the lower value of the maximum possible years in prison after selecting the corresponding option. This value is stored on the ‘PB’ variable and ‘Max’ and ‘Min’ are the maximum and minimum possible values for ‘PB’. The fourth parameter of the rule is a list with the properties (in form of literals) of the plan to consider in the calculus. Lines 4 and 5 contain the possible options after the event, that is the plans with this triggering event. The plans annotations correspond to the parameters to determine the “personal benefit” and the risk associated. Risk values are two numbers arbitrarily selected. What is important is the relative relation between plans risks (the ‘p_silence’ plan is more risky considering the best solution according to Nash equilibrium). Another issue to add is that the triggering event (‘+decide’), is acquired as a percept: `decide(cooperationpayoff(2), defectpayoff(1), delatorpayoff(0),temptationpayoff(3) [emotions (fear,hope,joy)]` [2] that has the most common emotions we have considered for this situation. The *agentB* is similar to *agentA*, but in this case he doesn’t have expectations.

[1]Both the fulfillment and violation conditions are explicitly modeled on expectations because we take an “open world” assumption so if a negation of a belief is not explicitly declared, then the agent has no information about if it is true or false.

[2]Values extracted from (Ashlock and Rogers, 2008)

```
1 expect__("silence",FullfilCond,
     ViolateCond,EventFunctor):-
     FullfilCond=silence(decision)
          [source(agentB)] &
     ViolateCond=betray(decision)[
     source(agentB)] & EventFunctor="+
     decide".
2 pb_max(PB, Max, Min, [max_years(MY)])
     :- (not .ground(MY)|MY>0) & Max=3
     & Min=0 & PB=Max/MY.
3
4 @p_betrayal[max_years(2),risk(0.3)]
     +!decide (...) <- (...)
5 @p_silence[max years(3),risk(0.5)]
       +!decide (...) <- (...)
```

Figure 2: Appearance of the Jason implementation of the *agentA* agent in the prisoner dilemma.

The values for the parameters of the personality profiles were defined according to (Santos et al., 2010). A set of four combination of values were used. These four personality types are: social, troubleshooter, negotiator, and realistic. Some combination of these personality profiles produced the following results:

A social, B troubleshooter: A silence, B betrayal
A social, B negotiator: A silence, B silence
A social, B realistic: A silence, B betrayal
A social, B social: A silence, B silence

Coherently with the personality types chosen, in this experiment the social agent tends to be cooperative (keeping silence). The troubleshooter and realistic tend to be more pragmatic betraying the other prisoner and the negotiator takes risks looking for benefits and remains in silence (cooperates).

Trust Game (TG)

Another important sequential game is the the trust game (Berg et al., 1995). In this game a proposer (or *trustor*) is being given an amount of endowment to be split and shared with the *trustee*. The amount shared is multiplied by a factor (usually three) and then the *trustee* decides to give back any amount. This way the *trustor* hopes to receive something back related to it’s initial offer trusting in the intentions of the other. In real situations both players tend to share more than what would be predicted in the game perfect equilibrium: “no trust” (Bracht and Feltovich, 2008).

The game was implemented similar to PD. In this case, the *trustor* perceives `decide(endowment(10))[emotions(hope)]` from the environment, expects a fair offer from the *trustee* (around the half) and his personal benefit is max-

```
Trustor
@p_1st[rest(75),risk(0.3)]+!decide(...)
@p_2nd[rest(60),risk(0.4)]+!decide(...)
@p_3rd[rest(45),risk(0.5)]+!decide(...)
@p_4th[rest(30),risk(0.5)]+!decide(...)
Trustee
@p_1st[offer(20),risk(0.1)]+!offer(...)
@p_2nd[offer(30),risk(0.2)]+!offer(...)
@p_3rd[offer(40),risk(0.4)]+!offer(...)
@p_4th[offer(50),risk(0.6)]+!offer(...)
```

Figure 3: Appearance of the Jason implementation of the *trustor* and *trustee* agent in a trust game.

imized when he gives a fair offer. Moreover the *trustee* has no labeled percepts or expectations, and his personal benefit is maximized if he offers as less as possible. The possible options for both players are shown in figure 3. The parameters for the *trustor* are what he keeps in percent after sharing (rest) and risk, and for the *trustee* are what he offers from the triplied endowment received in percent, and risk. Again the values have no real meaning but the relative relation between them. The combination of some personality profiles and the configuration described previously produced the following results:

A social, B troubleshooter: A 55%, B 40%
A social, B negotiator: A 55%, B 40%
A social, B realistic: A 55%, B 40%
A social, B social: A 55%, B 50%
A troubleshooter, B social : A 35%, B 50%
A negotiator, B social: A 55%, B 50%
A negotiator, B realistic: A 55%, B 40%
A troubleshooter, B realistic: A 35%, B 30%

Similarly to the PD, in the TG the social agent behaves in a cooperative way and offers a high quantity (55% as trustor or 50% as trustee). The troubleshooter and realistic are prudent showing a pragmatic behavior (35-40% and 30-40% respectively), and the negotiator takes risks offering always more than the minimum allowed (55-40%), but remaining prudent.

6 DISCUSSION AND CONCLUSIONS

In this work we used an open agent affective architecture to build emotional agents that must simulate situations of strategic decision-making influenced by affective issues. We have used several widely accepted supporting psychological theories in order to contribute to an incremental line of research in the field of emotional computing. We have also made our own propositions and assumptions to fill uncovered gaps overlooking a final implementation. These initial results demonstrate in first place that there are evidences that we can reach a diverse, believable and closer to humans behavior when including an emotion mechanism in an agent. The behavior of O3A agents in some classical games is more like the behavior of humans in real situations compared to agents that doesn't include emotions. Between the affective issues modeled, personality seems to produce more variability on results, what is quite consistent with a real situation. Nevertheless using iterated versions of the games may change the result and would help to better tune the overall design. In the proposed design the influence of agents interactions on emotions is given by the use of 'expectations about others' and 'personal benefits' related to others, which produces emotional reactions associated to interactions. Nevertheless we aim to improve existing structures and to create new ones in order to offer more realistic simulations of the human decision process.

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Companies do not come to faster decisions by osmosis â€" it is always the result of a better decision-making framework. In agile organisations, the ability to make nimble decisions lead to 2.5x the growth, twice the profit, and a 30% higher ROI on investments. How can you unlock your ability to make better, smarter decisions? When it comes to strategy, creating a polarized choice is sometimes helpful. Because you will fill in the details around a general plan, your pathways can be mutually exclusive. From here, you can not only make a decision more easily, but you can make it faster as well. Below is an effective framework for strategic decision-making and tools that you can use to ensure you get decision-making right. Framework for Strategic Decision-Making. Intuitive- emotional approach is opposed to rational decision-making. Managers sometimes decide to do something because it feels â€œrightâ€.Â Strategic decision-making process is so strategic that each firm has its own approaches to these strategic decision-making. Good many alternative approaches have come into practice because each firm is unique or strategic.Â Strategic decision making involves the usual decision-making processâ€"specific objectives derived from organizationâ€™s strategic intent, search for alternatives to achieve those objectives, evaluation of these alternatives, and choice of the most appropriate alternative. Thereafter, this choice is put into action. Existing research shows that emotions affect the decision making of the agent and make it appear more human-like. In game industry, emotions of players and non-players characters have not been paid...Â Cite this paper as: Chen W., Carlson C., Hellevang M. (2011) Emotional Agents in a Social Strategic Game. In: KÃ¶nig A., Dengel A., Hinkelmann K., Kise K., Howlett R.J., Jain L.C. (eds) Knowledge-Based and Intelligent Information and Engineering Systems. KES 2011.