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Conceptual and Computational Analysis of the Role of Emotions and Social Influence in Learning

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Abstract

In this paper it is analysed how emotions and the social environment affect active and reflective learning processes. First a conceptual analysis is made using recent insights from Cognitive, Affective and Social Neuroscience on the roles of emotions and social interactions on learning. Next, a computational analysis is made using a computational model of learning processes following these insights. In this analysis neural mechanisms for the impact of both a person's own emotions and the emotions of others are taken into account. In particular, it is considered how these impacts work for different learning types, such as active or reflective learners. The analysis shows how the impacts of emotions and social interaction strengthen the learning process. It is discussed how from these insights indicators can be obtained that can be used to design technology-enhanced learning environments able to exploit these impacts.

Keywords: emotion, learning, social, reflection

1. Introduction

Recently it has been advocated that new insights for learning and teaching can be gained from findings in Cognitive, Affective and Social Neuroscience (e.g., Immordino-Yang and Fischer, 2011). In particular, this has been put forward for the role of emotions and social interaction in learning (e.g., Immordino-Yang & Damasio, 2007; Immordino-Yang & Faeth, 2010). In the current paper the purpose is to explore this line in a more specific manner by contributing neurologically based conceptual and computational analyses on how emotions and social environment influence learning, in particular in relation to different learning styles such as reflective and active learners (Felder & Silverman, 1988, Felder & Brent, 2005). Such analyses are a useful basis to provide guidelines and support for the design of technology-enhanced learning environments facilitating emotions and social interactions that contribute to the learning process.

First, using relevant findings from a number of neurological theories (e.g., Damasio, 1999; Immordino-Yang & Damasio 2007; Moore & Haggard, 2008; Iacoboni, 2008; Hebb, 1949) on the role of emotions, reflection and social contagion in behaviour and learning, a qualitative causal model was designed and used for a conceptual analysis. Next, by refinement and formalisation a dynamical computational model was obtained and used for a number of simulation experiments. In these experiments, the role of emotions, reflection and social interactions on active and reflective learning styles were explored in more detail. It was shown how affective states contribute to effectiveness of a learning process, thereby creating a personal and emotionally grounded awareness experience for the learner. To increase learning effects, a learner has to feel involved in and attached to the elements in a learning process by experiencing ownership and responsibility for own choices and behaviour, and more generally (e.g., Kolb & Kolb, 2005). To achieve this, experiencing affective states relating to behaviours and becoming aware of them in a reflective manner form an important part of a learning process. In particular, this may concern an affective state related to valuing a specific option for how to address an issue (or problem) before deciding to choose for it. Moreover, it may concern feeling satisfaction (or lack thereof) about a chosen approach after it was executed to address the issue. These feelings may provide emotionally grounded prior and retrospective awareness of such options, and thus may strengthen learning by reinforcing choices with positive evaluation. In a social

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context co-learners do not only interact in a cognitive sense but also by transferring affective states. Facilitating on the one hand the experience and exchange of emotions, and on the other hand stimulating awareness of these emotions, is an important basis for emotionally grounded forms of reflection and can make an essential contribution to the learning

The reported work has identified several useful elements from the neurological domain concerning the learning process, such as Hebbian learning, internal simulation, interaction of emotion and cognition, emotion-related valuing of decision options, awareness states and reflection, mirroring and social contagion of emotion. It has been found that based on these elements a conceptual and computational dynamical model can be developed that provides insight in the role of emotions and social interactions in learning processes. Furthermore, the model was shown to be useful in conducting a variety of simulation experiments displaying how emotions and social interaction can strengthen different types of learning processes.

The neurological findings identified have been shown to provide a useful source for both conceptual and computational analyses of learning processes, and the role of emotions, reflection and learning. Based on these findings, the proposed approach offers guidelines and support for the development of technology-enhanced learning environments facilitating the role of emotions, reflection and social interaction in learning.

In this paper, first in Section 2 relevant neurological literature is briefly summarised. Based on this, in Section 3 a conceptual model is discussed, which is used for a conceptual analysis and some guidelines in Section 4. In Section 5 the conceptual model is formalised to a computational model and used for computational analysis based on simulation experiments, thereby detailing the conceptual analysis. Finally, Section 6 is a discussion.

2. Recent neurological insights relevant for affective and social influences in learning

Recent developments in Cognitive Neuroscience have revealed mechanisms behind the generation and contagion of affective states, and the roles they play in mental processes involved in generating behaviour. In this section they will be briefly reviewed.

2.1. Prior and retrospective awareness of behaviour

For learning processes based on experiences for a certain action or behaviour it is often emphasized that awareness of ownership and valuing of such experiences is of crucial importance. For example: ‘To learn experientially learners must first of all own and value their experience’ (Kolb & Kolb, 2005, p. 207). In recent neurological literature mechanisms responsible for developing awareness of an action are reported (e.g., Moore & Haggard, 2008; Voss, Moore, Hauser, Gallinat, Heinz, & Haggard, 2010). A distinction is made between awareness prior to execution and retrospective awareness. *Prior awareness* is, among others, based on prediction of effects of a prepared action. In *retrospective awareness* in addition the monitored execution of the action and the sensed actual effects play an important role (e.g., Moore & Haggard, 2008; Treur, 2011). Prior awareness plays an important role in valuing action options and choosing or initiating the actual execution of an action. Retrospective awareness plays an important role in reflection on one’s own functioning in order to learn from the consequences of a choice that was made, and make adaptations in valuation of the option for the future.

To obtain prior awareness of an action, *internal simulation* is used as a means for prediction of the (expected) effects of a prepared action (e.g., Haggard, 2008; Wolpert, 1997). The idea behind internal simulation is that in a certain context (which may cover sensed aspects of the external world, but also internal aspects such as the own goals and attitudes) preparation states for actions are activated, which through prediction links in turn activate sensory representation states for (predicted) consequences of the action. Such an internal simulation process can go on in an arbitrary depth. The notion of internal simulation has a longer tradition, for example in the context of prediction of effects of prepared motor actions (Becker & Fuchs, 1985), imagination (Hesslow, 2002), processes related to emotional responding (as-if body loops; Damasio, 1994, 1999), and reading another person’s mind (Goldman, 2006). Usually the predicted effects of a prepared action are valued. If this valuation is satisfactory, this may entail a ‘go’ decision for the actual execution of the action option, thus exerting control over action execution. In contrast, predicted effects valued as less satisfactory may lead to a ‘no go’ decision.

Over the years the idea has developed that *retrospective action awareness* is based on some form of co-occurrence of predicted effects and sensed actual effects. Traditionally, this co-occurrence was described by a ‘comparator model’ (e.g., Feinberg, 1978, Wolpert, 1997). More recently it has been analysed that the predicted effect and the sensed actual effect are in fact not compared but added to each other in some integration process (e.g., Moore & Haggard, 2008; Voss et al., 2010; Treur, 2011).

2.2. The role of emotions in awareness and valuing of behaviour

Awareness of behaviour has a strong emotional component. This relates both to the valuing of behaviour options before deciding and in retrospect after a behaviour. In recent neurological literature this has been studied in relation to a notion of value as represented in the amygdala (e.g., Bechara, Damasio, & Damasio, 2003; Bechara, Damasio, Damasio, & Lee, 1999; Morrison & Salzman, 2010; Rangel, Camerer, & Montague, 2008). In opting for a particular behaviour, experiences with the environment (from the past) play an important role. In a retrospective process, taking into account the experiences the valuations (and their related emotions) of behaviour options are adapted through learning processes. This is a form of adaptation of the agent to the environment as reflected in these past experiences. Parts of the prefrontal cortex (PFC) and other areas in the human brain such as the hippocampus, basal ganglia, and hypothalamus have extensive, often bidirectional connections with the amygdala (e.g., Ghashghaei, Hilgetag, & Barbas, 2007; Morrison & Salzman, 2010; Salzman & Fusi, 2010). A role of amygdala activation has been found in various processes involving emotional aspects (e.g., Murray, 2007). Usually emotional responses are triggered by stimuli for which a predictive association is made of a rewarding or aversive consequence, given the context including the person's goals. Feeling these emotions represents a way of experiencing the value of such a prediction, and to which extent it is positive or negative. In this sense the felt emotions strongly relate to prior valuation of an option. Similarly, feelings of satisfaction are an important element of retrospective valuation of what is experienced after behaviour has been chosen. These affective aspects of the concept of value form a point of departure of current work on the neural basis of decision making processes and economic choice in neuroeconomics (e.g., Bechara et al., 2003; Bechara et al., 1999; Morrison & Salzman, 2010; Rangel et al., 2008; Sugrue, Corrado, & Newsome, 2005).

2.3. Emotion contagion impact on behaviour

Above it has been discussed how emotions relate to awareness of behaviour. In this subsection it is discussed how in a social context a learner's processes can be strengthened by the affective states of others. Affective states can play an important role as their occurrence in one person (a co-learner or tutor) can easily affect the same affective state in a learner, for example, for the emotions related to (prior) valuations of behavioural options, and emotions related to (retrospective) valuation concerning effects of chosen behaviour. In a social context, the idea of emotion-related valuing can be combined with recent neurological findings on the *mirroring function* of certain neurons (e.g., Iacoboni, 2008; Rizzolatti & Sinigaglia, 2008). Mirror neurons are neurons that, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions and a function to represent states of other persons. They are active not only when a person intends to perform a specific action (or body state), but also when the person observes somebody else intending or performing this action or body change. Indeed, if states of others are affecting some of the person's own states that at the same time are connected via neural circuits to states that are crucial for the person's own feelings and actions, then this provides an effective mechanism for persons to fundamentally affect each other's actions and feelings. As mirror neurons make that some specific sensory input (an observed person) directly links to the relevant own preparation states, mirroring is a process that fully integrates mirror neuron activation states in the on-going internal simulation processes. This includes expressing emotions in body states, such as facial expressions. This mechanism of mirror neurons and internal simulation thus provides a neural basis for emotion contagion.

Given the general principles described above, this mirroring function provides a mechanism by which emotions felt in different individuals about a certain considered behaviour mutually affect each other, and, assuming emotion-related valuing, in this way affect how by individuals behaviour options are valued. This means that both prior awareness of actions and retrospective awareness of behaviour can be affected by emotion contagion.

2.4. On the role of reflection in behaviour

It is widely accepted that reflection plays an important role in most learning processes (e.g., Moon, 2004). Reflection can take place with respect to multiple aspects of a learning process, for example, on the learned knowledge or behaviour itself, on emotions, on goals and motivation, or on the planning over longer time periods. Reflection on such different aspects contributes to an awareness of a personal and emotionally grounded experience for the learner. This avoids a type of learning process in which a learner acts in a detached manner involving hardly conscious reactive patterns in response to environmental cues that happen to be offered over time, as sometimes suggested in a behaviourist perspective on learning (e.g., Skinner, 1968). Here an opposite perspective on learning is adopted according to which learner is aware of and experience ownership and responsibility for his or her own choices and actions. Reflection covers (mental) activities during a learning process that contribute to this. The learner's environment can stimulate such mental activities, for example, in the form of a tutor or coach asking specific questions that my provoke reflection, or a co-learner asking for explanation or displaying a specific behaviour and emotion.

In the conceptual and computational model used in this paper reflection regarding behaviour being learned is addressed. More specifically, it concerns reflection of the behavioural choices made to address encountered situations. This reflection is expressed by awareness of different options and their valuations prior to choosing one of them, and (in retrospect) awareness of the valuation of the chosen option after a choice was made and executed. On the one hand this perspective is in line with Damasio (1999)'s notion of *core consciousness*, which is based on the feeling of emotions and noting how these emotions are associated to a situation or object. This approach fully integrates emotions and reflection. On the other hand it adopts the idea of multiple unconscious states and processes which occur in parallel and compete to become part of consciousness; see, for example, Dennett (1991)'s *multiple draft model*, and Baars (1997)'s *Global Workspace Theory*. The Global Workspace Theory was developed to describe how a single flow of conscious experience can result from a large multiplicity of parallel (unconscious) processes. The general idea is that a *winner-takes-it-all competition* takes place to determine which of these processes will get dominance and will be included in the single flow of consciousness.

2.5. The Hebbian perspective on learning

In the above summary, no learning or adaptation of behaviour over time was discussed yet. This element is discussed here. In (Hebb, 1949) a principle was put forward describing how the strength of a connection between two states is adapted over time based on simultaneous activation of the two states ('neurons that fire together, wire together'). The principle goes back to Hebb (1949), but has recently gained enhanced interest by more extensive empirical support (e.g., Bi & Poo, 2001) and more advanced mathematical formulations (e.g., Gerstner & Kistler, 2002). This quite simple principle turns out to be very useful in practice to explain or computationally model learning processes, and will be used in the conceptual and computational model below. In relation to what is described above, the principle can be applied to the connections from sensory representations of stimuli to preparation states, and to the connections from preparation states to the associated (predicted) feeling states. Given the mechanisms of internal simulation and valuing described above, by adapting such connections the activations of specific behaviour options can change over time.

3. Conceptual model for the role of emotions and social influence in different types of learning processes

The analyses made in this paper assume a learning process where the learner encounters multiple items or situations over time for which decisions for an appropriate approach or behaviour have to be learned. Such learning processes are quite general; they occur in diverse contexts, varying, for example, from learning to address mathematics or physics problems by choosing effective approaches, to learning to undertake appropriate actions in the context of developing a healthy lifestyle. The contributed analyses address how emotions and social interactions affect this type of learning process. More specifically, learning processes are considered in which, for a specific context, a learner learns to choose between certain options (for actions or behaviours) to address a specific issue, for example, to solve a problem or to undertake a certain action. In accordance with what was discussed in Section 2, affective states play an important role in specific processes such as:

- valuing different options before choosing one of them
- experiencing a certain level of satisfaction when a chosen option leads to a state in accordance with the learner's goals
- experiencing a certain level of prior and retrospective awareness of behavioural choices made (reflection)
- feeling adequate levels of self-confidence and motivation

3.1. A Conceptual Model

In this section the conceptual model is used as a basis for conceptual analysis of the role of emotion and social influence in learning; see Figure 1 for an overview.

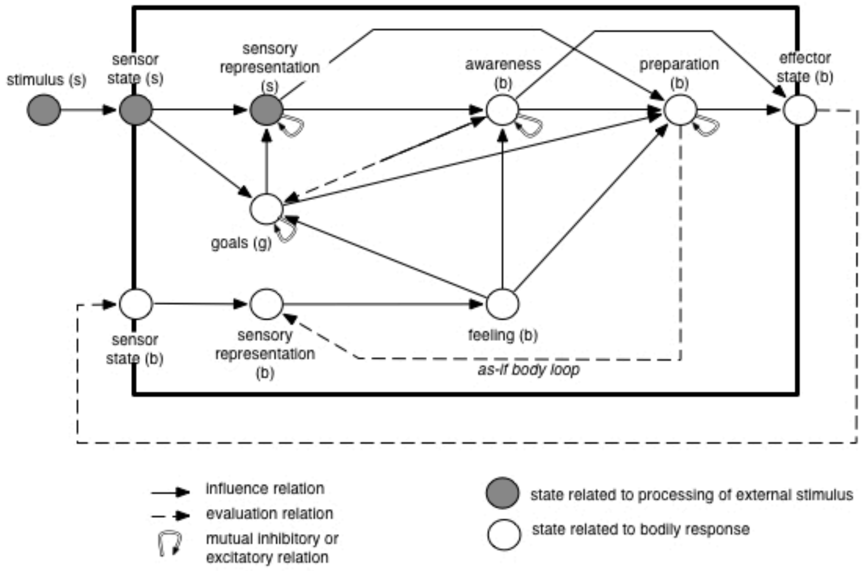

Figure 1 A conceptual model for emotions and social influence in learning

3.1.1. Sensory representations and preparation states

For the model an encountered item is indicated in an abstract manner by a number of *stimuli* s_i. Note that these s_i may refer to multiple aspects and elements in reality, such as the elements of a mathematical problem description, or the different aspects of a context of a person in a healthy lifestyle development process. As a first step in the process, via the sensor states for s_i the learner generates internal *sensory representations* for the stimuli s_i indicating an encountered item. Such internal representations have associations (of different strengths) to *preparation states* for a number of alternative options b_k to address the item, on which a decision has to be learned. In this decision making two further elements play an important role: the feeling state associated to the option b_k, and the (reflective) awareness state for the option b_k.

3.1.2. Associated feeling states

Before performing an action, *feeling states* for the options b_k are affected by *predictive as-if body loops* (cf. [8, 9]) via the sensory representation states for b_k. This corresponds to the notion of internal simulation (as described in Section 2) that results in a degree of prior awareness regarding a prepared action and its expected outcome. The as-if body loop predicts this evaluation value prior to execution of an action and by this valuing provides an important impact on the decision to be made. This valuation depends on the strength of the feeling associated to this option, which is represented by the strength of the connection from preparation state for b_k to sensory representation for the option b_k. After performing an action for b_k, by an *external execution loop* the feeling state associated to b_k is affected as well via the effector state for b_k, expressing execution of option b_k, the sensor state for b_k and the sensory representation state for b_k. Through these sensory states the action result is observed, which plays the evaluative role of retrospective awareness. The *evaluation value* is determined by the activation level of ther sensor state for b_k which depends on the connection strength of the link from the effector state for b_k to the sensor state for b_k. High connection strength means success of the chosen option and low strength failure (in satisfying the learner). In short, the feeling state combines the prior awareness of the predicted effect and the retrospective awareness of the sensed actual effect, thus complying with the findings in (Moore and Haggard, 2008; Voss et al., 2010), as addressed in Section 2.

3.1.3. Hebbian learning

In the model the connection strengths of two types of connections are adapted by *Hebbian learning* (Hebb, 1949): from sensory representation state for s_i to preparation state for b_k (adapting direct associations), and from preparation state for b_k to sensory representation state for b_k (adapting the associations to feelings). As Hebbian learning depends on the activation levels of the connected states, a positive evaluation of a performed action has a positive effect on the learning, as in this case the sensory representation state for b_k gets a higher activation level. When by the Hebbian learning mechanism the connection strength from the preparation state for b_k to the sensory representation state for b_k has increased, this implies that for a next occasion when the item is encountered the valuing of the option before a decision is made will be higher. In addition, through the sensory representation state for b_k and the feeling state for b_k, the preparation state for b_k gets a higher activation value as well, which, via Hebbian learning, increases the strength of the connection from sensory representation state for s_i to preparation state for b_k. This way, both the direct association between represented stimulus and preparation, and the association between preparation and feeling used for valuing are adapted during the learning process.

3.1.4. Reflection
The activation of an *awareness state* for a behaviour option b_k results in a degree of awareness for this option (prior or retrospective for the behaviour), as a way of modelling reflection. Activation of an awareness state not only depends on the sensory representations for the s_i but also on the feeling state associated to the option b_k and the active goals g the person has. The connection between feeling and awareness state models the reflective influence of the feeling state for b_k. This way the resulting awareness is grounded in feeling an emotion, in line with (Damasio, 1999). Moreover, the awareness states for different options are in competition with each other due to mutual inhibiting connections, following the perspectives of (Baars, 1997; Dennett, 1991). Purely reactive and other non-conscious responses to stimuli bypass the awareness states and are modelled by the direct links from goals and sensory representations to preparations. The awareness state thus serves a similar function as the global workspace in Global Workspace Theory, where sensory representations can be passed on to the global workspace and a competition determines which content then becomes conscious; cf. (Baars & Franklin, 2009).

3.1.5. Impact of social interaction
The effects of *social interaction* have their basis in the fact that the learner senses the expression of options by others: some of the stimuli s sensed the learner are actually stimuli $s_{B,bk}$ that indicate expression states for option b_k of another agent B; see Figure 2. Such a specific type of stimulus indicates the extent to which option b_k and their associated emotions are expressed by this agent B. For agents B in contact with the considered learner, these emotions are assumed to be sensed and represented by the learner using sensor states and representation states for $s_{B,bk}$. As a form of mirroring a representation state for agent B's expressed option b_k has impact on the agent's own preparation state for b_k for the same option via the connection between the representation state and preparation state; see also Section 2.

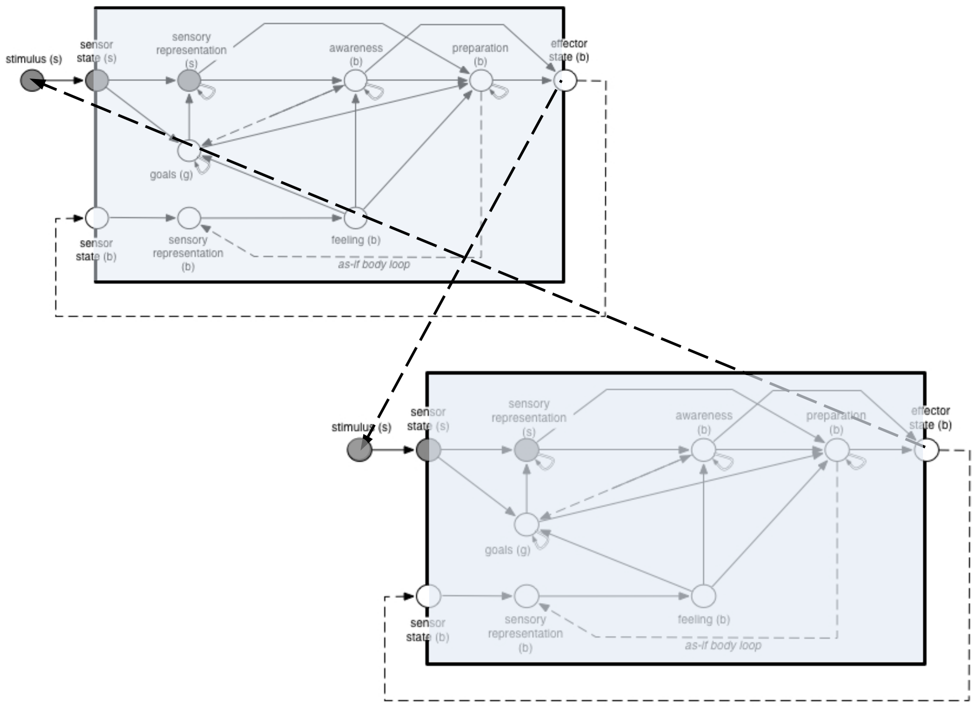

Figure 2 Interaction between two learners

By this connection the preparation state for b_k gets the *functionality as a mirror neuron*: it is not only activated when the learner him or herself prepares for the action, but also when another agent performing the action is observed. As a second effect, in the model the sensory representation state for agent *B*'s expression of the option b_k also affects the awareness state for the option b_k. This models a direct way in which interaction with another agent about an option stimulates to become (more) aware of the option. Thus the effect of social interaction on reflection is modelled in two ways: through the latter direct association, and through the mirroring process via the as-if body loop using the preparation, sensory representation and feeling states for b_k.

4. Conceptual analysis and guidelines for specific characteristics of learners and learning processes

In this section a conceptual analysis of the model is given by examining how the model is able to account for different learning phenomena and learner types as identified by literature. Some guidelines will be provided on how the model can be used to describe and simulate these learning processes.

4.1. Different types of learners

In their 1988 paper, Silverman and Felder identified a variety of learning styles based on the notion that learning is a two-step process involving (i) the reception and (ii) the processing of information (Felder & Silverman, 1988). One of the dimensions of learning styles addressed in their work concerns active and reflective learning styles; see also the Felder Index of Learning Styles (e.g., Felder & Silverman, 1988, Felder & Brent 2005). This dimension originates from a learning style model developed by Kolb (Kolb, 1984). Recently, the Kolb model has seen some major revisions (Kolb & Kolb, 2005). It includes a new 9 learning style typology, sharing the same underlying assumption addressed in (Felder & Silverman, 1988) that learning involves (i) a grasping experience (i.e., reception of information) and (ii) a transforming experience (i.e., processing of information). A further distinction is made: grasping experiences are defined by the dimension of *experiencing* (feeling) and *conceptualizing* (thinking), while transforming experiences are defined by *action* and *reflection*. These different individual abilities for how to grasp and transform information can be combined to result in a learning space with different learning types. Individuals' learning style positions them in this space according to the two dimensions. Each dimension is determined by a combination of individual characteristics and environmental factors. Note that individuals can have abilities to a certain degree, or have abilities that lie on both ends of one dimension (for example, being able to balance feeling and thinking). These dimensions can also be regarded as different parts of a learning cycle, showing a learner's preference for one part of the cycle. A simplified overview of this combined learning space can be seen in Figure 3.

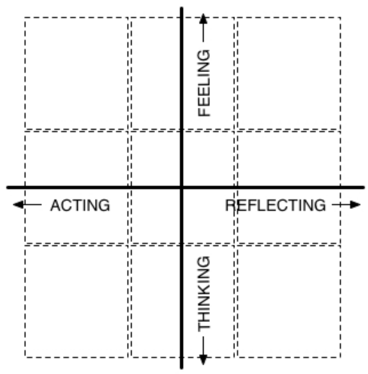

Figure 3 Simplified representation of the learning dimensions and the 9 learning styles from Kolb & Kolb, 2005.

Although these learning style dimensions are continuous and should not be regarded as either/or categories, the extremes are very effective to describe behavioral patterns. The poles of the dimensions describe persons with a strong preference or ability for that type of grasping or processing. In the remainder of this subsection, these poles will be used to show how the corresponding learning abilities relate to the conceptual model presented, and how this model can help to understand the dimensions more fully.

First, learners who have *feeling* as dominant grasping learning ability rank high on the experiencing dimension and act on gut feelings rather than on logical analysis. Intuitive experience is often more important to them than processing the concrete representations. In the model, this relates to strong connections to and from the feeling states (see Figure 4, left-hand side). Information that is received will have a strong influence on (associated) feelings, which is represented by strong connections from the sensory representation (of *b*) states to the feeling states. Feelers are also more easily aware of intuitive emotions, represented by strong connections between de feeling states and the awareness states. Their emotions have a grounded influence on which goals and behaviour options get high activation levels, shown in strong connections between the feeling states and the goal and preparation states.

Second, learners with strong *thinking* abilities prefer to solve problems and make decisions based on finding solutions to questions. They grasp information by focusing on the symbolic complexity of a problem and prefer abstract conceptualizations. In the model this corresponds to enhanced awareness represented by the awareness states where conscious content is shaped (see Figure 4, right-hand side). That is, the sensory representation (of *s*) states, where internal representations of the stimuli and context are developed, have a strong connection to the awareness states, which in turn strongly influence the preparation states. Furthermore, the direct connections from the awareness states to the effector states are strong, enabling the thinker to let his or her actions be informed mostly by conceptual and symbolic representations, with a smaller part to play for the associated feelings.

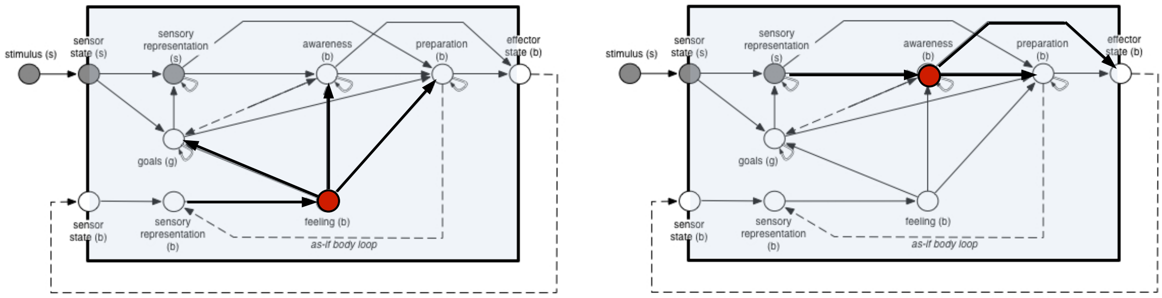

Figure 4 Modelling a feeler (left-hand side) and thinker (right-hand side)

Third, learners with dominant *reflective processing* abilities have good capacities to internally reflect on the received information. They often need time to think things through in order to process the perceptual complexity of stimuli into abstract concepts. Reflectors are good in generating ideas and come up with different approaches, but they are careful to translate them into actions. In the model, these learning abilities can be represented by an initially already stronger internal loop (which by learning is strengthened further) from preparation to sensory representation (of *b*) states through which the person is able to perform mental simulations and predictions of action consequences (see Figure 5, left-hand side). This reflector's chain of thought based on internal simulation strongly influences the action options that become active.

Last, learners with a preference for *acting* in order to process information are more comfortable with, or better at, active experimentations. Testing and trying provides them with insights and they are able to learn from hands-on experience. For active learners, the connections from the preparation states to effector states, from the effector states to the sensor states (of *b*), and from these sensor states to the corresponding sensory representation states are strong (see Figure 5, right-hand side). Through their evaluations the actions inform further information processing. Furthermore, since actors often feel less comfortable with reflection and prefer to start exploring the behavioural aspects of a problem, in the model the connections between the sensory representations and the preparations states are strong, bypassing the awareness states.

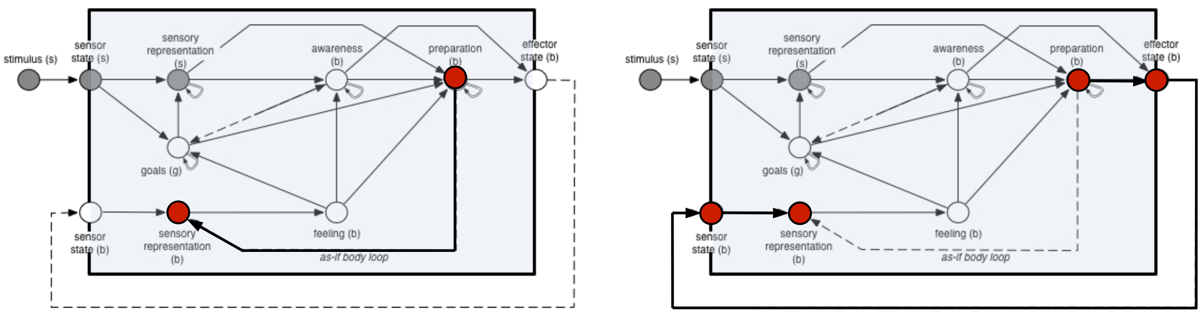

Figure 5 Modelling a reflective learner (left-hand side) and active learner (right-hand side)

The model thus provides a framework for analysis of the factors that determine a learner's experience and learning type. It can also be used as a tool to reason about the consequences of learning a different learning style (for example: a reflector who is being exposed to an educational setting in which active experimentation is required), or about the consequences of interactions between learners with different learning styles. For example, it appears that active learners prefer to work in groups, while reflective learners prefer to work alone or with a single familiar partner (Felder & Spurlin, 2005). Furthermore, teams with members with diverse learning styles among the members perform significantly better than teams with all members with the same learning style (Wolfe, 1977), and teams made up of members whose learning styles were balanced among the four learning modes performed better on a critical thinking task than teams whose members had specialized learning styles (Kayes, 2002). The model introduced in this paper can be used to create and analyze these and other scenarios of groups of leaners with different capabilities. This will be discussed in Section 5, based on a computational model that can be used for simulation.

4.2. Guidelines for enabling conditions

The conceptual model described in Section 3 has as its purpose to provide a basis for analysis and for design technology-enhanced learning environments in which emotions and their contagion are an important driving force. In such an environment, enabling and monitoring are key elements. In order to monitor and analyse in how far certain emotions occur and in how far they are transferred between different persons in a learning process, a number of technical devices can be used. In the area of affective computing usually the focus is on individual emotions and methods to measure or estimate them, for example, by sensing and interpreting face expressions, voice expressions, heart rate, or skin conductivity. Such methods can be used as far as they are not too obtrusive. However, the focus of the presented approach also covers the role of social interaction and the way in which emotions are transferred from one learner to another learner, or between a tutor or (virtual) coach and a learner. Therefore, more specifically, emotion transfer is to be enabled by the environment offered, and monitoring of this transfer should be incorporated. This means that different forms of interactions need to be analysed on their emotional content, for example, by recognition of figurative language and linguistic analysis, or, in case of direct visual interactions or the use of video connections, by analysis of face expressions.

Not all emotions that are exchanged are relevant in general, but specifically when they are associated to particular types of mental states. Relevant examples of such mental states are:

- emotions related to prior awareness and valuation of behaviour options
- emotions related to retrospective awareness and valuation of chosen behaviour (satisfaction)
- emotions related to goals
- emotions related to attitude aspects

One important impact is that due to emotion contagion the related mental states are strengthened, and because of that the associations between feeling and option are strengthened. Moreover, other relevant types of impact are experiencing and showing empathic understanding for such a state, and (through interaction) making aware the experiencing of the emotion felt, which is a contribution to reflection. Also these elements have an amplifying effect on the learning. Table 1 provides an overview of examples of these types of impacts. To be able to make use of the impacts of emotions in technology-enhanced learning, conditions can be identified enabling these effects, and for monitoring the transfer of the emotions. Table 2 shows an overview of examples of such aspects. Note that part of this is the organisation of the social network of learners: how they are connected.

Table 1 Emotion impact: strengthening a mental state M, reflection on M, and empathy for M

for mental state M	**type of interaction**	**strengthening mental state M**	**empathic understanding for mental state M**	**strengthening reflection on M**
• prior valuation of behaviour options (intentions) • retrospective valuation of chosen behaviour (satisfaction) • goals (long-term, short-term) • attitude aspects (e.g., beliefs)	emotion impact from learner to learner	display of emotion for M: • nonverbal (face expressions, emoticons; e.g., ☺,☹,😐,👍,👎) • verbal (emotion-loaded language in speech and written form)	nonverbal and verbal display of the other person's emotion and verbal acknowledgement of recognition of the other person's emotion in relation to M (face expressions, emotion-loaded language, emoticons)	verbal interaction to make the learner aware of M via the experienced feeling (talking, writing on M)
	emotion impact from virtual coach to learner	virtual display of emotion in relation to M: • nonverbal (virtual face expressions, emoticons) • verbal (virtual emotion-loaded speech and text messages)	virtual nonverbal and verbal display of the learner's emotion and virtual verbal acknowledgement of recognition of the learner's emotion in relation to M (virtual face expressions, emoticons, virtual speech and virtual text messages about the learner's emotion in relation M)	virtual verbal interaction on M (virtual speech and virtual text messages about M)

Table 2 Enabling and monitoring different types of emotion impact

emotion impact	**verbal emotion impact**			**nonverbal emotion impact**			**for mental state M**
	examples	***enabling***	***monitoring***	***examples***	***enabling***	***monitoring***	
from learner to learner	emotion in speech	audio connection	acoustic and linguistic speech analysis	face expressions	video connection	emotion recognition from faces	• prior valuation of behaviour options (intentions) • retrospective valuation of chosen behaviour (satisfaction) • goals (long-term, short-term) • attitude aspects (e.g., beliefs)
	emotion in text messages	textual connection	linguistic text analysis	graphical indications: mood scores, emoticons	connection for graphical objects	interpretation of graphical objects	
from virtual coach to learner	emotion in virtual speech	synthesizing speech with emotions	from generation	virtual face expressions	connection for graphical objects	from generation	
	emotion in virtual text	automated generation of text with emotions	from generation	graphical indications: mood scores, emoticons	connection for graphical objects	from generation	

5. Computational analysis of the role of emotions and social influence

Modelling causal relations discussed in neurological literature in the manner as presented in previous sections and Figure 1 does not take large numbers of specific neurons into consideration but uses more abstract mental states. By this abstraction neurological knowledge is lifted to a mental (cognitive/affective) modelling level. The type of learner model that results shows some technical elements also used in the neural modelling area. More specifically, it takes states as having a certain activation level in the interval [*0*, *1*] (instead of binary states), which, for example, makes reciprocal cognitive/affective loops possible. The modelling approach adopted from (Treur and Wissen, 2012) exploits techniques used in continuous-time recurrent neural networks, in line with what is proposed in (Beer, 1995). In particular, for a state causally affected by multiple other states, to obtain their combined impact, first the activation levels V_i for these incoming states are weighted by the respective connection strengths ω_i thus obtaining $X_i = \omega_i V_i$, and then these values X_i are combined, using a combination function $f(X_1, .., X_n)$. In this case, a combination function based on a logistic threshold function has been chosen:

$$f(X_1, .., X_n) = \left(\frac{1}{1+e^{-\sigma(X_1+\cdots+X_n-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right)(1+e^{-\sigma\tau})$$

Table 1 shows which impacts contribute to the value of the different states (as can also be observed from Fig. 1) at any time point t.

Table 3 Overview of the Impacts on States

state	**notation**	**impacts on this state**	**combined impact: Σ activation value . connection strength**
stimulus s	$stim(s_i)$	-	-
sensor state for s	$ss(s_i)$	$stim(s_i)$	$stim(s_i) \cdot \omega(stim(s_i), ss(s_i))$
sensory representation for s	$srs(s_i)$	$ss(s_i)$, $goal(g_k)$, $srs(s_j)$	$ss(s_i) \cdot \omega(ss(s_i), srs(s_i)) + \Sigma_k\, goal(g_k) \cdot \omega(goal(g_k), srs(s_i)) + \Sigma_j\, srs(s_j) \cdot \omega(srs(s_j), srs(s_i))$
awareness state for b	$as(b_k)$	$srs(s_i)$, $goal(g_j)$, $feel(b_k)$, $as(b_m)$	$\Sigma_i\, srs(s_i) \cdot \omega(srs(s_i), as(b_k)) + \Sigma_j\, goal(g_j) \cdot \omega(goal(g_j), as(b_k)) + feel(b_k) \cdot \omega(feel(b_k), as(b_k)) + \Sigma\, as(b_m) \cdot \omega(as(b_m), as(b_k))$
goal for g	$goal(g_g)$	$ss(s_i)$, $as(b_k)$, $feel(b_k)$, $goal(g_f)$	$ss(s_i) \cdot \omega(ss(s_i), goal(g_g)) + as(b_k) \cdot \omega(as(b_k), goal(g_g)) + feel(b_k) \cdot \omega(feel(b_k), goal(g_g)) + \Sigma_f\, goal(g_f) \cdot \omega(goal(g_f), goal(g_g))$
sensor state for b	$ss(b_k)$	$es(b_k)$	$es(b_k) \cdot \omega(es(b_k), ss(b_k))$
sensory representation for b	$srs(b_k)$	$ss(b_k)$, $prep(b_k)$	$ss(b_k) \cdot \omega(ss(b_k), srs(b_k)) + \Sigma_k\, prep(b_k) \cdot \omega(prep(b_k), srs(b_k))$
feeling for b	$feel(b_k)$	$srs(b_k)$	$srs(b_k) \cdot \omega(srs(b_k), srs(b_k))$
preparation state for b	$prep(b_k)$	$srs(s_i)$, $as(b_k)$, $goal(g_g)$, $feel(b_k)$, $prep(b_m)$	$\Sigma_i\, srs(s_i) \cdot \omega(srs(s_i), prep(b_k)) + as(b_k) \cdot \omega(as(b_k), prep(b_k)) + \Sigma_g\, goal(g_g) \cdot \omega(goal(g_g), prep(b_k)) + feel(b_k) \cdot \omega(feel(b_k), prep(b_k)) + \Sigma_m\, prep(b_m) \cdot \omega(prep(b_m), prep(b_k))$
effector state for b	$es(b_k)$	$as(b_k)$, $prep(b_k)$	$as(b_k) \cdot \omega(as(b_k), es(b_k)) + prep(b_k) \cdot \omega(prep(b_k), es(b_k))$

5.1. Dynamics of activation levels of states

Using the above combination function, dynamics of the activation levels of states are described by:

$$V(t+\Delta t) = V(t) + \gamma\,[\, th(\sigma, \tau, <combined\_impact>) - V(t)\,] \cdot \Delta t$$

Here <combined_impact> is the combined impact as specified in the last column of Table 1. Note that $\omega(X, X) = 0$ is assumed as a convenient notation. Parameter γ is an update speed parameter.

5.2. Dynamics of connections based on Hebbian learning

For the connections from $srs(s_i)$ to $prep(b_k)$ and from $prep(b_k)$ to $srs(b_k)$ their strengths are adapted using the following *Hebbian learning rule*, taking into account a maximal connection strength *1*, a *learning rate* η, and an *extinction rate* ζ (usually taken small):

$$\omega(prep(b_k), srs(b_k))(t+\Delta t) = \omega(prep(b_k), srs(b_k))(t) + [\eta\ prep(b_k)(t).\ srs(b_k)(t).(1 - \omega(prep(b_k), srs(b_k))(t)) - \zeta\ \omega(prep(b_k), srs(b_k))(t)]\ \Delta t$$

$$\omega(srs(s_i), prep(b_k))(t+\Delta t) = \omega(\ srs(s_i), prep(b_k))(t) + [\eta\ srs(s_i)(t).prep(b_k)(t).\ (1 - \omega(\ srs(s_i), prep(b_k))(t)) - \zeta\ \omega(\ srs(s_i), prep(b_k))(t)]\ \Delta t$$

A similar Hebbian learning rule can be found in (Gerstner & Kirstler, 2002, p. 406]. By the factor $1 - \omega(prep(b_k), srs(b_k))(t)$ (resp. $1 - \omega(\ srs(s_i), prep(b_k))(t)$) the learning rule keeps the connection strengths bounded by *1* (which could be replaced by any other positive number); Hebbian learning without such a bound usually provides instability. When the extinction rate is relatively low, the upward changes during learning are proportional to the activation levels of both connected states and maximal learning takes place when both are *1*. Whenever one of these activation levels is *0* (or close to *0*) extinction takes over, and the connection strength slowly decreases (unlearning).

5.3. Computational analysis based on simulation experiments

This subsection describes simulation experiments that were performed in order to demonstrate the how the computational model described above can be used to analyse the dynamics of the modelled learning processes in a more detailed manner. For the experiments, a scenario is considered with two learners: Alice and Bob. Alice and Bob both try to learn an appropriate response to a stimulus (for example, a proper approach to a mathematical problem). For the sake of simplicity, here it is assumed that there is one appropriate response to the stimulus, namely behaviour b_1 (with expression denoted as $es(b_1)$), that Alice and Bob are learning. The activation level of this expressed behaviour b_1 is considered an indication of how well this behaviour has been learnt, seen from an externally observable perspective. From an internal perspective, the strengths of the connections from stimuli representation for s_1 to preparation states for b_1 and from preparation to feeling states for b_1 are considered indications of how well the behaviour has been learnt. In relation to these indications, the learning speed relates to the steepness of the graphs of the activation levels of these states and connection strengths over time. The simulations provide a closer look at the dynamics of leaners with different feeling and thinking capabilities. The parameter settings used for these simulations (and for all other simulations described in this work) can be found in Table 2 and 3. Note that the extinction rate is chosen 0 in order to clearly demonstrate the learning process without unlearning or forgetting.

Table 2 Threshold and steepness values used in the simulation scenarios

	ss(s)	srs(s)	goal	as	ss(b)	srs(b)	feel	prep	es
threshold τ	0.5	0.4	0.6	0.6	0.5	0.4	0.4	1	0.4
steepness σ	6	4	2	3	4	2	3	3	2

Table 3 Parameter values used in the simulation scenarios

parameter	value
learning rate η	0.2
extinction rate ζ	0
update speed γ	0.5

5.3.1. Effects of feeling capabilities on learning

First the case is considered in which Alice and Bob have different learning styles with respect to feeling. For Bob feeling is a dominant learning style; in the model his feeling states are strongly connected to his sensory representation states and his awareness, goals and preparations states ($\omega = 0.9$, see also Section 4.1, Figure 4). In contrast, Alice does not include her feelings much in the learning process, which is modelled by very weak connections to and from her feeling states ($\omega = 0.1$). An overview of the connection values can be found in Table 4. Note that the inhibitory and excitatory relations of competing states are 0, as for these scenarios only one proper behaviour option is considered with no competing goals or awareness states.

Table 4 Connection weight values used for a learner with feeling capabilities.
Highlighted double entries are used to indicate personalized settings and are of the form <A, B>.

from	to	stim	ss(s)		srs(s)		goal	as	prep	ss(b)	srs(b)	feel	es
			ss1 (stim)	ss2 (es other)	srs1	srs2							
	stim	-	1	0									
ss(s)	ss1 (stim)		0	0	1		0.8						
	ss2 (es other)		0	0		1	0.5						
srs(s)	srs1				0	0		0.6	0.5				
	srs2				0	0		0.6	0.5				
goal					0.2	0	0	0.2	0.2				
as							0.2	0	0.5				0.5
prep									0		0.1		0.8
ss(b)										-	0.8		
srs(b)											0	<0.1, 0.9>	
feel							<0.1, 0.9>	<0.1, 0.9>	<0.1, 0.9>			-	
es			0	nonsocial: 0 social: 0.8						1			-

As literature indicates that a good performing learner has capabilities across all dimensions (e.g, Kayes, 2002, it is expected that Bob would learn faster and better than Alice. In Figure 6 all state activations can be seen for Alice and Bob. This simulation shows how Alice and Bob perform when learning separately, which explains why there is no activation in the sensor input and representation states of another learner (ss(es_1) and srs(s_2)); see also section 3.1.5. The fact that Bob has a dominant feeling strategy can clearly be deduced from the activity in the feeling state (feel(b_1)), which shows regular activity for Bob, but hardly any for Alice. Consequently, the goal, awareness and preparation activations are all significantly higher for Bob than they are for Alice. The same holds for the resulting effector state (es(b_1)) that represents the action and for its valuation states (ss(b_1) en srs(b_1)). Figure 6 also shows that the association between preparation and sensory representation states used for valuing (ω(prep(b_k), srs(b_k))) reaches its optimal value of 1 quicker for Bob than for Alice. In sum, Bob will reach higher activation levels for the appropriate response and will learn the corresponding valuations quicker than Alice.

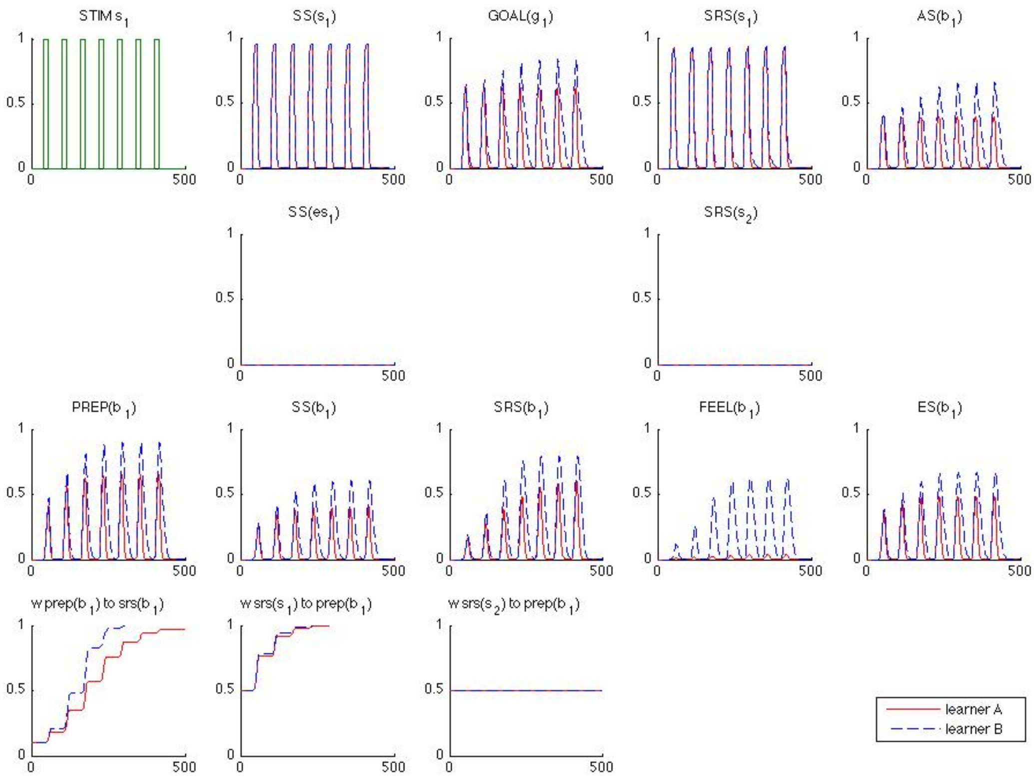

Figure 6 Non-social learning of Alice (low feeling capabilities) and Bob (high feeling capabilities)

It is now examined how Alice and Bob influence each other's learning process when learning together. Inspired by Wolfe (1977)'s work in which it was observed that teams with diverse learning styles among the members perform better than teams with all members with the same learning style, it was hypothesized that learning together will strengthen Alice's learning as she is able to benefit from the feeling capabilities of Bob. Figure 7 shows the simulation results. The sensor and sensory representation state for another learner (ss(es_1), srs(s_2)) now show different activation levels for Alice and Bob: Alice receives a high activation level from the observed effector state from Bob, whereas Bob receives somewhat lower activation levels resulting from the lower effector state of Alice. Overall, even though Alice still has little to no feelings that are associated with the stimulus, she now has higher activation levels for her goal, awareness and preparation states, resulting from the incoming activation that is the result of observing Bob. Consequently, her effector states show higher activation levels when learning together than when learning separately: es(b_1) has activation levels of 0.48 versus 0.59, respectively. Also, the learning association ω(prep(b_k), srs(b_k)) is optimized faster than when learning alone. Bob maintains his high activation and learning levels.

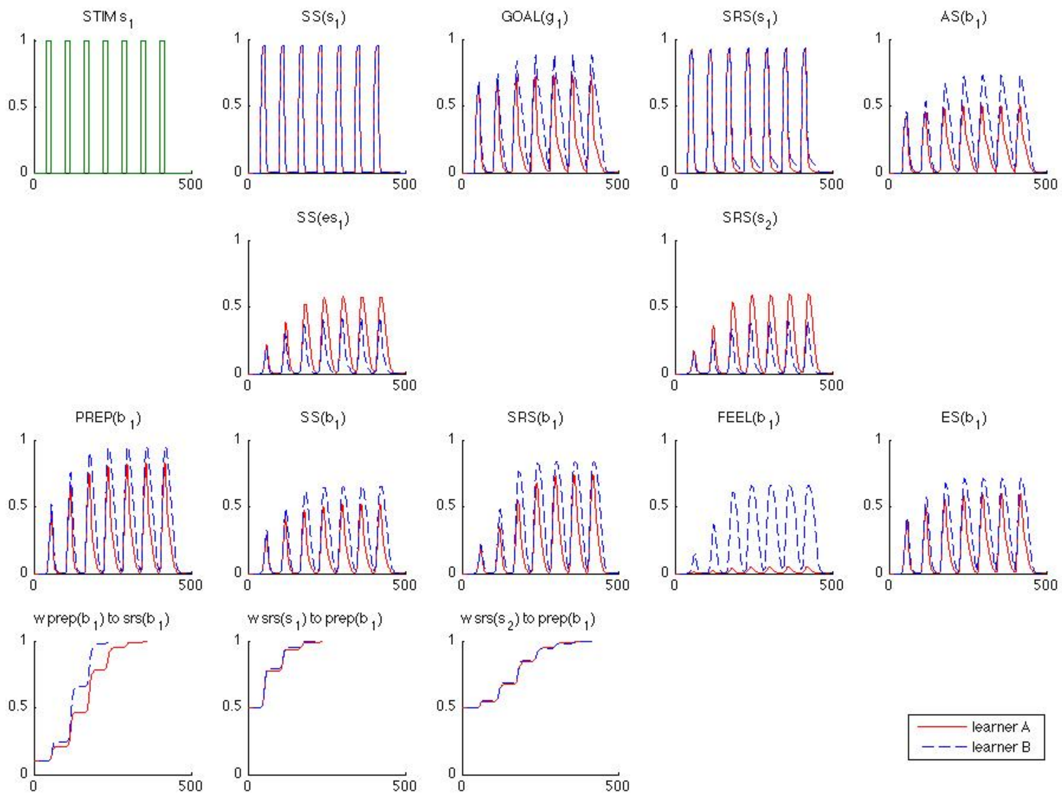

Figure 7. Social learning of Alice (low feeling capabilities) together with Bob (high feeling capabilities)

5.3.2. Effects of thinking capabilities on learning

Another pair of simulations was performed to analyse the effects of different thinking capabilities. In this scenario, Bob has thinking as a dominant learning style, indicated by strong incoming and outgoing connections of the awareness state (ω = 0.9). Alice on the other hand has trouble to grasp the symbolic or abstract conceptualizations of a problem. She has weak connections to and from her awareness state (ω = 0.1).

Figure 8 shows the activation levels of Alice's and Bob's states when learning separately. The difference between Alice and Bob is striking: Bob reaches high activation levels for his states, while the low awareness state for b_1 (as(b_1)) of Alice do not contribute to any activation, resulting in very low activation for her effector state for b_1 (es(b_1)). When looking at the results from Hebbian learning (the three graphs at the bottom of Figure 8), it can be seen that the learning process for both the adaption to direct associations between sensory representations of stimuli s_i and preparations for b_k (ω(srs(s_i), prep(b_k))) and the adaption of the connection from preparation to feeling b_k (ω(prep(b_k), srs(b_k))) has much slower progress for Alice than for Bob. It is clear from this simulation that the awareness state plays a crucial role in the learning process.

When learning together, a similar pattern as for the feeling simulations can be observed. From Figure 9 it is clear that although Alice's awareness state still has low activations, her other states are far more active, resulting in a much higher effector state ($es(b_1)$, increased from 0.29 to 0.44). The Hebbian learning of the connections is faster. In short, learning together involving observing Bob's behaviour, helps Alice to be a better learner.

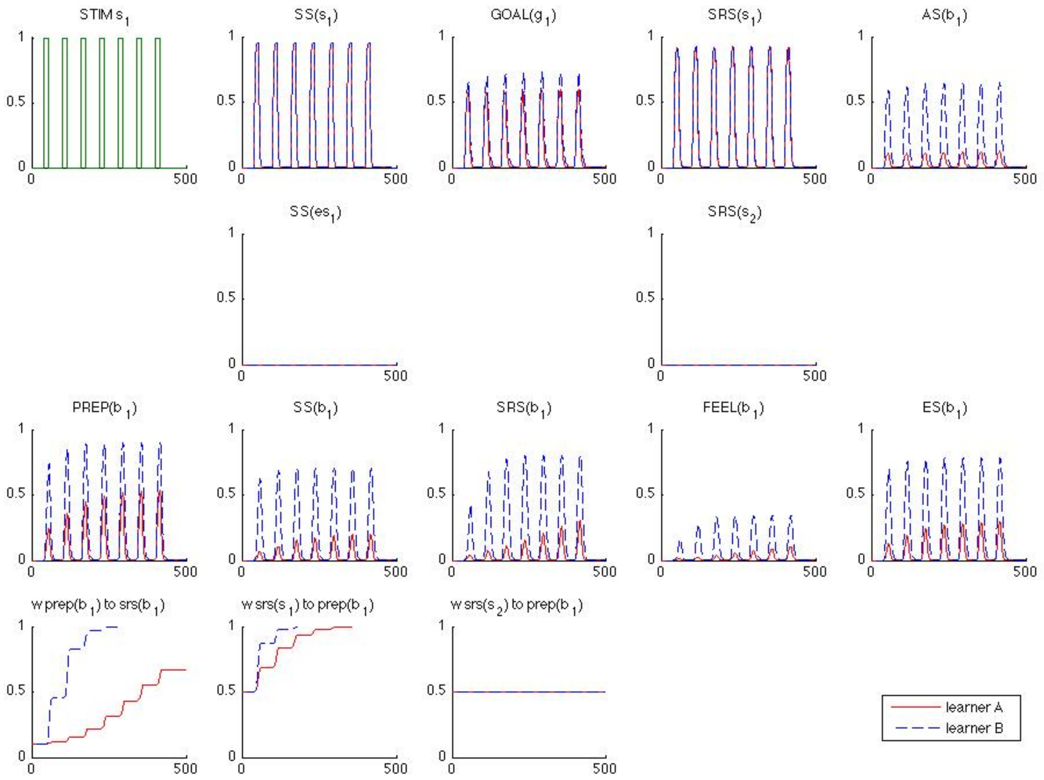

Figure 8. Non-social learning of Alice (low thinking capabilities) and Bob (high thinking capabilities)

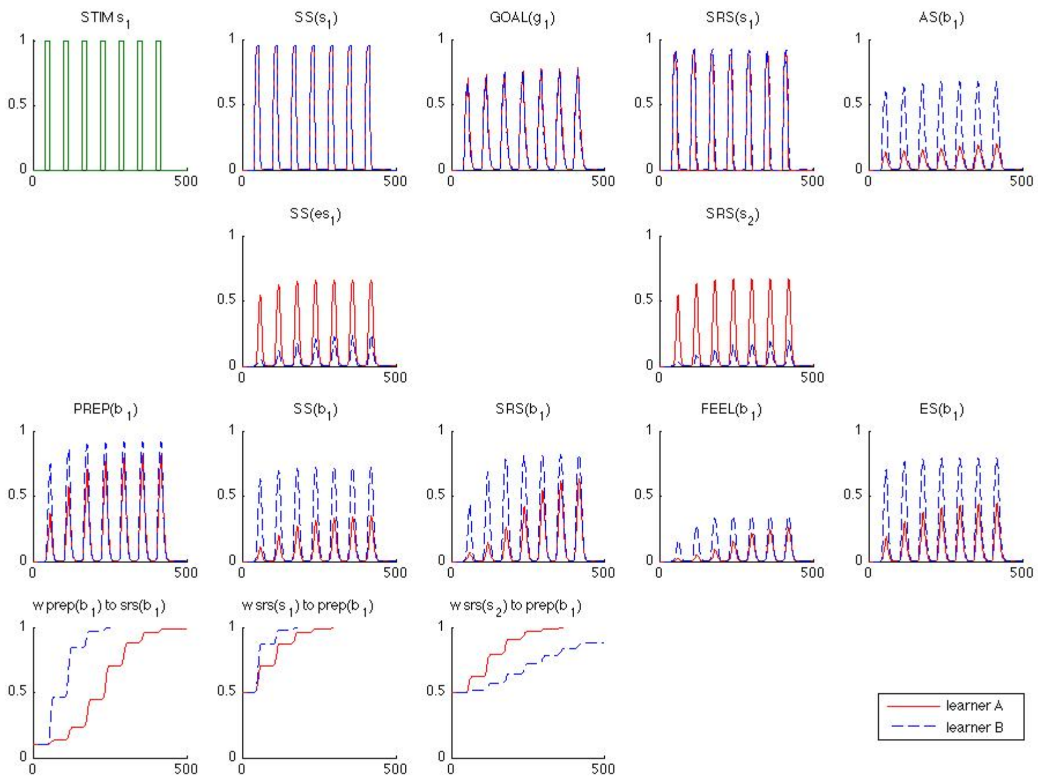

Figure 9. Social learning of Alice (low thinking capabilities) together with Bob (high thinking capabilities)

5.3.2. Effects of learning together on individual learning

In more detailed simulation experiments it has been investigated how beneficial it is for a reasonably good thinking style learner to interact with another thinking style learner. The social interaction effect differs for different strengths of thinking style learner A (let's call her Alice again) upon learner B (Bob) with a thinking style component of 0.7. In Figure 10 it is shown that when the learning process is long enough, the final effect on the behaviour of Bob is limited. The base line for Bob for learning his behaviour without social interaction is *0.66*, and by social interaction this can be increased to *0.76*, depending of the strength of Alice as a thinking style learner. So in this respect the social interaction provides a modest benefit for Bob, even when Alice performs worse than he does.

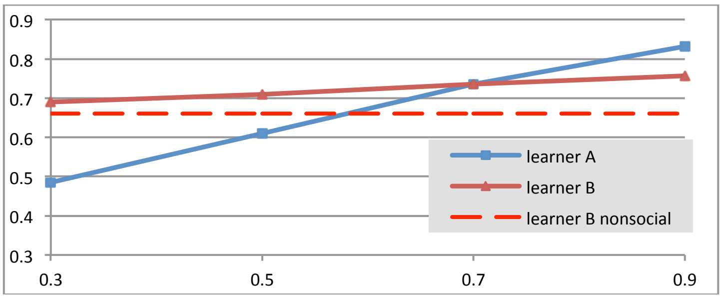

Figure 10 The effect of different strengths of a thinking style of learner A (horizontal axis) on the behaviour strength for A and B (vertical axis)

It has also been analysed how fast the learning proceeds with different strengths of a co-learner. The results are shown in Figure 11. The figure shows the time duration that is elapsed before reaching connection strength *0.8* for the two connections that are adapted by Hebbian learning. The graph at the left-hand side shows the connection from preparation to sensory representation of *b.* A substantial reduction the learning time of Bob occurs when the strength of the thinking style of Alice is above *0.7,* which is the strength of Bob's thinking style. Note that for the nonsocial case this duration is *178* time units. These results seem to indicate for these specific circumstances that without social interaction almost the same behaviour can be learned, but the time to learn the same level of behaviour may be substantially longer without social interaction. However, the graph at the right-hand side for the connection from sensory representation of the stimulus *s* to preparation of *b* shows no reduction of the learning time of Bob. Here for the nonsocial case the duration to reach a learning rate of 0.8 is *59* time units, which is the same for both Alice and Bob in the social scenario when they have a thinking style component larger than 0.7. One explanation could be the case that 59 time units is the optimal speed of learning for all learners with a dominant thinking style. An alternative hypothesis is that learners with a strong thinking component do not rely heavily on direct processing of information from the sensory representations to the preparation nodes and optimization takes place elsewhere.

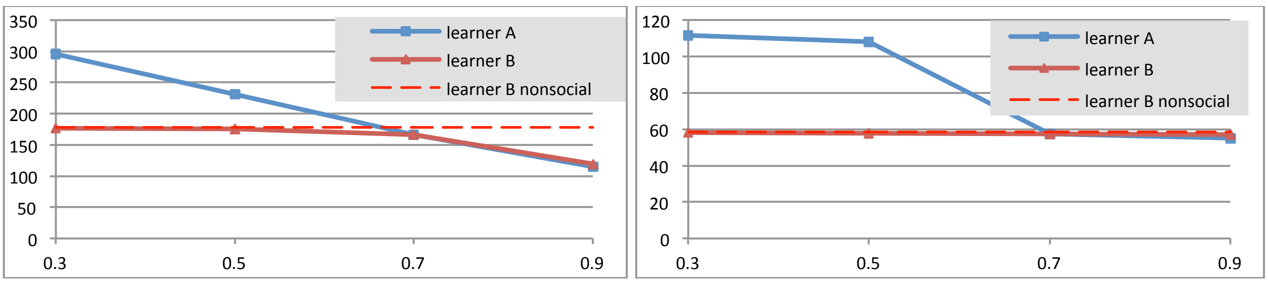

Figure 11 The effect of different strengths of a thinking style of learner A (horizontal axis) on the learning time for A and B: number of time units to reach connection strength *0.8* (vertical axis) for the connection from preparation to sensory representation of *b* (left-hand side), and for the connection from sensory representation of stimulus *s* to preparation of *b* (right-hand side).

6. Discussion

The perspective followed in this paper is in the spirit of what is advocated in (Immordino-Yang & Damasio, 2007; Immordino-Yang & Faeth, 2010). An important difference is that the latter work is informal and rather general whereas in the current paper the ideas are more focused, formalised and analysed both in a conceptual and computational manner for specific types of learners. The conceptual and computational models are based on recent neurological insights concerning a number of relevant processes: internal simulation (e.g., Damasio, 1994), interaction of emotion and cognition, emotion-related valuing (e.g., Bechara et al, 2003), awareness states and reflection (e.g., Baars, 1997), mirroring and social contagion of emotion (e.g., Iacoboni, 2008; Rizzolatti and Sinigaglia, 2008) and Hebbian learning (e.g., Hebb, 1949). For example, the models used are in accordance with recent neurological insights that processing (and interpreting) of sensory information (grasping) and preparing for actions are often not isolated from each other, but in principle are strongly intertwined processes (e.g., Pulvermüller and Fadiga, 2010).

The basic learning model includes elements of stimulus-response association learning (for the connections between stimuli representations and preparation states) as known from the behaviourist tradition (e.g., Skinner, 1968), but extends this substantially by providing possibilities to integrate emotional elements in the learning process (for the connections between preparations and feelings), and of how these are affected by social contagion of emotions. Furthermore, the model incorporates a notion of awareness of actions as a basis for the roles of thinking and reflection in learning. Learning together as addressed here means that both learners learn and can observe each other’s learning process and behaviour. Note that cases in which one learner, in a kind of tutor role, explicitly provides help to another learner were not addressed in the model. Although the reported experiments have been designed to illustrate the principles of the approach for two interacting learners, they can easily be extended to larger groups of learners. An issue for further research may be to investigate more extensively by computational analysis how exactly learning results depend on different combinations of learning styles present in groups with more members.

The conceptual model and the computational model provide means to analyse learning processes with different types of learners, more specifically the effect of emotions and social interaction on these processes. In particular they provide a basis for the design and testing (in silico, by simulation) of technology-enhanced learning environments that enable and support emotions in individual and social contexts. Simulations as performed in section 5 can inspire new hypotheses and specifications of learning theories.

The model provides two types of indications for how well behaviour has been learnt: from an externally observable perspective and from an internal perspective. From the external perspective the activation levels of expressed behaviours (upon offering the stimuli) are considered an indication. From the internal perspective, the strengths of the connections from stimuli representation to preparation states for the behaviour, and from preparation to feeling states for the behaviour are considered indications of successfulness of the learning process. Moreover, indications for the learning speed are found in the steepness of the graphs of the activation levels of these states and connection strengths over time. Note that the internal and external perspective need not provide the same indications. Based on the given models, it might well be the case that learners based on modest internal connections show good results in externally observable behaviour, or conversely, that learners with strong internal connections that show less strong observable behaviours. This may be an issue for further research.

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