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EMOTIONAL SCAFFOLDING WITH RESPECT TO TIME FACTORS IN NETWORKING COLLABORATIVE LEARNING ENVIRONMENTS

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ABSTRACT

With regard to learning, emotional considerations have been included in the research agenda for a long time and literature offers a variety of studies evaluating the role of emotions in different settings (class, tests and exams, studying at home, etc.). This knowledge and experience has tentatively begun to endow intelligent network systems with emotion assessment and affective feedback capabilities, although the process is still in its infancy. This paper reviews emotional aspects in learning and affect recognition as well as feedback strategies. In the described strategies, the need for considering the time factor is also stressed.

KEYWORDS

Emotion awareness, Affect detection, Affective feedback, CSCL, Social networks, Time factor

INTRODUCTION

Advances in Computer Supported Collaborative Learning Systems (CSCL) and Social Networks enable students to select their own teacher (schoolteacher, another peer, another system, etc.), their own curriculum, their own "assessors" (Laurillard, 2009). Due to the vast development of Networks and Telecommunications, users are able to form either small or large groups with common targets and needs, developing a kind of *Collective Intelligence*, a shared or group intelligence that emerges from the collaboration and competition of many individuals.

However, just because an environment makes it technologically possible, this does not mean that social interaction will necessarily take place. Perhaps, innovative Human Computer Interactions (HCI) models focus exclusively on cognitive factors, and are often unable to adapt to real-world situations in which affective factors play a significant role (Kort & Reilly, 2002). Humans have strong emotions emanating from deep instincts of survival *with,* as well as *against* others. Emotions strongly influence human behaviour in social conditions and must be seriously considered when forming collaborations.

Kreijns, Kirschner, & Jochems (2003) identified the main pitfall in CSCL environments as a tendency to restrict social interaction to educational interventions aimed at cognitive processes, while social (psychological) interventions aimed at socio-emotional processes are ignored, neglected or forgotten. Students need to trust each other, feel a sense of warmth and belonging, and feel close to each other before willfully engaging in collaboration and recognizing collaboration as a valuable experience (Rourke, 2000).

This process requires time. In building challenging social interactions and effective networks, time limits work obtrusively.

Appropriate affective scaffolds entail sacrifices in immediate academic performance, and this is something common in expert teachers. Should expert systems do the same?

If we wish to build real personalisation systems, it is necessary to consider not only user preferences, but also the user's emotional/affective state (Picard, 1997). There is a need to build intelligent network systems that are sensitive to the user's emotions, and which intelligently respond to these emotions, in real educational settings and with sufficient time. We need to address research questions about the association of properties of users' networks (size, density, timing) with expression of emotions in their social interactions. We need to conduct studies that will search for possible associations between the users' emotions (joy, sadness, etc.) in their social interactions and their engagement in learning over time.

Incorporating emotional awareness (sensing and responding to the user's emotions) into Computer Systems and Networks can offer a more interactive and challenging learning environment, satisfying the learners' demands for empowerment, social identity, and an authentic learning experience.

In the last two decades, there have been different updated endeavours to model the management of emotions and affectivity in Intelligent Systems. A thorough testing of user's emotional transitions over time may lead to more precise results.

CONSIDERING EMOTION

Emotion, together with cognition and motivation are key components in learning (D'Mello et al., 2005). A purely cognitive approach that does not take into consideration emotions, motivations, and the like, paints an artificial, highly unrealistic view of real minds. Minds are neither purely cognitive nor emotional; they are both and more (LeDoux, 2000). We learn from sources of information that we bother to pay attention to (Davou, 2000).

NEUROLOGICAL EVIDENCE

There is extensive literature on the study of emotions, with a wide range of perspectives: evolutionary, behaviourist, componential, socio-cultural and now, neuro-scientific (Afzal & Robinson, 2007). Neurology provides us with a neuro-biological approach to emotions, focusing on the emotional operations of autonomous and basal neurotic systems (e.g. the limbic system). The latest research findings point to activity in different brain areas, when positive, as well as negative emotions are experienced.

For example, Davidson, Scherer & Goldsmit (2003) indicate that the Dorsolateral Pre-Frontal Cortex guides decision-making through positive emotions (joy, hope, pride) and is critical for goal achievement decisions, while negative emotions such as threat, fear or anger reveal activity in the amygdala in the Limbic System.

J. Ledoux's (1996) systematic research underlines the privileged position of the amygdala; a point where everything converges. Sensory signals move from the hypothalamus to the amygdala in 15 milliseconds and from the hypothalamus to the cortex in 25 milliseconds. A stimulus is firstly, and above all, appraised if it is a threat (Goleman, 1995). As a result, negative emotions such as fear or anger are triggered before the Pre-Frontal Cortex has even received the signal to be processed. Negative emotions take precedence in perception over positive ones.

The amygdala has limited pattern recognition capabilities compared to the cortex, and performs "a quick and rough" pattern recognition and response. A stimulus is firstly, and above all, appraised if it is a threat. The amygdala has presumably been structured in answer to one critical question for survival: "*Do I eat it or does it eat me? The brain is able to sense fear before a human can think of it" (Daniel Goleman).*

POSITIVE VS. NEGATIVE EMOTIONS

Despite evidence of the beneficial effects of a positive mood and emotions there are no clear rules such as: positive emotions foster learning, and negative emotions are detrimental (Hascher, 2010). A student with a positive disposition would see an F on a math test as evidence that he needs to work harder, while another may see it as evidence that he is stupid (Goleman, 1995). In general, there are no adequate empirically proven strategies to address the presence of emotions in learning, especially negative ones. A theoretical background has been built upon theoretical foundations of pedagogy/affect, as well as recommendations made by pedagogical experts (D'Mello, et al. 2008).

According Pekrun's, et al. (1992, 2006) findings, a positive mood fosters holistic, creative ways of thinking. Harmful effects can only be expected in situations, where students are in a good mood and the learning topics are of less importance to them. In this case, a positive emotion might detach them from learning.

Negative emotions, however, in most cases direct students' attention to themselves. Necessary attention for learning and task solving is lacking, because they try to find ways to get rid of the bad feeling (Hascher, 2010). When negative emotions create a pessimistic perceptual attitude, they divert the learner's attention to aspects irrelevant to the task, activating intrusive thoughts that give priority to a concern for wellbeing rather than for learning (Boekaerts, 1993).

Nevertheless, negative moods proved to enhance an analytical, detail-focused way of processing information. Curiosity and puzzlement may lead to investigate problems and frustration may lead to action, despite their negative valence (Heylen et al 2004). A state of confusion is sometimes considered positive for learning because students will be motivated to overcome the source of their misunderstanding. In literature, uncertainty is encountered as an "opportunity to learn" (Forbes-Riley & Litman, 2009).

Robinson, McQuiggan & Lester (2009) state that although, in general terms, students have a strong tendency to remain in the same affective state across time, when transitions to alternate affective states did occur, they followed interesting patterns. For instance, frustrated learners were very likely to transition to confusion or fear and were particularly unlikely to enter a positive state such as flow or excitement. Students experiencing a positive state of flow were likely to transition to confusion, which is still considered positive for learning and were unlikely to transition to the more negative state of frustration. Interestingly, confused learners were equally likely to transition to flow and frustration. These findings suggest that the affective state of confusion and its antecedents and consequences need additional study to determine which factors contribute to a positive transition to flow or a negative transition into frustration.

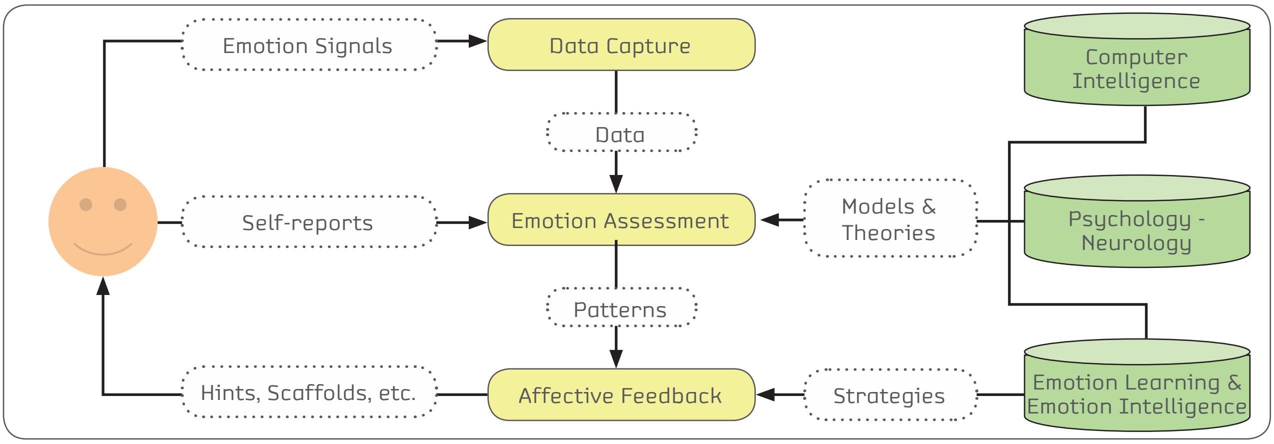
AFFECT RECOGNITION AND FEEDBACK

AFFECT DETECTION

Students are known to effectively engage and learn in their favourite social networks, where they exchange information and experiences with peers. These experiences are predominantly emotionally coloured. Social sharing of emotions occurs frequently in platforms such as Twitter and Facebook (Kivran-Swaine & Mor, 2011). People are compelled to share emotions shortly after they experience them, and find the sharing relieving.

Affective Computing (or Emotion Oriented Computing) has been focused on automated detection of affective states in a variety of contexts and it has shown promising results. By exploiting Computer Intelligence techniques, researchers are aiming at eliciting accurate automatic classifications of affective states and patterns, mostly in network interactions.

Figure 1. Emotion-assessment computer intelligent model



Consequently, affect measurement is usually grouped into three areas (Picard, 1997; Zimmermann, Guttormsen, Danuser, & Gomez, 2003):

- Psychological-Profiling tools (verbal/ non verbal self-reports, conductive chat, rating scales, standardized checklists, questionnaires, semantic and graphical differentials projective methods).
- Physiological signals-use of sensors (skin conductance-SC, electrodermal activity-EDA, electrocardiogram-ECG, blood volume pulse-BVP, electromyogram-EMG, respiration, pupillary dilation)
- Behavioral (facial expressions-face reader, voice modulation/intonation, hand tracking, body posture, motor behaviour-mouse-keyboard movements from log files, corrugator's activity).

In the majority of the studies, multimodal integration is applied (a combination of the three methods).

Computer intelligence can provide data-mining/ classification algorithms that can be trained by input data and emotion signals and through cluster analysis can produce accurate emotion classifiers. Classification categories like Neural Networks, Decision Trees, Bayesian Networks, Fuzzy Systems, Genetic Algorithms, etc. are mostly used. Table 1 below, evaluates the three areas of affect detection, describing benefits and drawbacks.

AFFECTIVE FEEDBACK

An ITS that is privileged with Affective Feedback capabilities, is able to send appropriate affective or cognitive signals to the user, in response to their affective state detection, thus ensuring their emotional safety and their engagement or persistence in the learning experience. In line with Hatcher's emotion's quality criteria (2010), the "appropriateness" of the response is further analysed in the following:

- ***Valence* of the response:** positive e.g. encouraging hints or neutral e.g. task-based feedback or no feedback at all. The case of negative response e.g. to reflect on user's confusion for activation purposes, requires quite high speculation and caution.
- ***Arousal* of the response:** activating, e.g. a drumbeat or de-activating like spiritual music or a short story.
- ***Timing* of the response**: immediately or after a fragment of time.
- ***Duration* of the response:** short e.g. a very short sound revealing success like in computer games or long e.g. a funny animation clip.

Affective feedback techniques also incorporate knowledge of student group characteristics (e.g., profile of cognitive skills, gender), to guide interference. In their experiment, Woolf, Burelson & Arroyo (2007) develop an agent tutor that customizes the choice of hint type for individual students based on their cognitive profile, gender, spatial ability, and math fact retrieval speed.

Although not extensive, there are remarkable studies that test methods and techniques of computer mediated affective feedback in network collaborations, and the impact that they have on users. A rough classification includes:

- *Dialogue moves* (hints, prompts, assertions, and summaries).
- *Immersive simulations* or *serious games*.
- *Facial expressions* and *speech modulations*.
- *Images, imagery, cartoon avatars, caricatures* or *short video-audio clips*

In some research studies, affect-adaptive computer tutors have been evaluated within

Table 1: Critical Review of Affect Detection Tools

Classification	1st-Class	Psychological		Physiological					Motor-Behavioral				
	2nd-Class	Verbal	Non-Verbal	EEG	ECG	BVP	EMG	EDA	Facial	Vocal	Body position-Gestures	Mouse-Keybord activity	
Criteria	Subjective	←	←	→	→	→	→	→	→	→	→	→	Objective
	Obtrusive	→	→	←	←	←	←	o	o	o	o	→	Unobtrusive
	Invasive	→	→	←	←	←	←	o	→	→	o	→	Noninvasive
	Out of Task	←	o	→	→	→	→	→	→	→	→	→	With task
	Expensive	→	→	←	←	←	←	←	←	←	←	→	Inexpensive
	Expertise	→	→	←	←	←	←	←	←	←	←	→	No-expertise
	Language & Culture-bound	←	→	→	→	→	→	→	→	o	→	→	Cross-cultural & language free
	Noisy	→	→	←	←	←	←	←	←	←	←	←	Clean
	Nonaccurate	o	o	→	→	→	→	→	→	o	→	o	Accurate

Range:

← Left Column

o Neutral

Right Column →

Classification criteria (adopted by Zimmermann, Guttormsen, Danuser, & Gomez, 2003; Wong 2006):

- **Objective/Subjective:** Relates to the degree of consciousness of the emotion that is experienced.
- **Obtrusive/Unobtrusive:** User's experience of the medium.
- **Invasive/Non invasive:** Realistic use in education setting.
- **Out of Task/In task:** Measurements are taken in parallel with user's task or not.
- **Expensive/Inexpensive:** The cost of the equipment needed.
- **Need Expertise/ No expertise:** In order to capture emotion signals.
- **Language & Culture-bound:** Cannot be used universally.
- **Noisy/Clean:** Data collected is "noisy" and need clarification or not.
- **Non-Accurate/ Accurate:** Additional variables must be considered.

a "Wizard of Oz" scenario, where a human "wizard" performs system tasks such as speech recognition, natural language understanding, and affect detection (Forbes-Riley & Litman, 2011). Machine learning optimization algorithms are applied in searching for policies for individual students, with the goal of achieving high learning and positive attitudes towards the subject.

Woolf, Burelson & Arroyo (2007) have used a variety of heuristic policies to respond to student's emotion. They measured how feedback variables interact to promote learning in context (characteristics of the learner, aspects of the task). Instructional feedback is varied according to type (explanation, hints, worked examples) and timing (immediately following an answer, after some elapsed time) (Shute, 2006). The socially intelligent system was found to yield increased student learning as compared to the control system. Wang et al. (2008) implemented a model of "socially intelligent tutoring" that achieved significant learning improvements, based on politeness theory in an online learning system.

TIME FACTOR-AFFECTIVE CHRONOMETRY

Emotions are not instantaneous, turning on or off at any particular point in time (Parkinson, 1995), but are dynamically changing over time. An emotional experience can last for only a couple of seconds up to several hours or even longer (Verduyn, Van Mechelen, & Tuerlinckx, 2011).

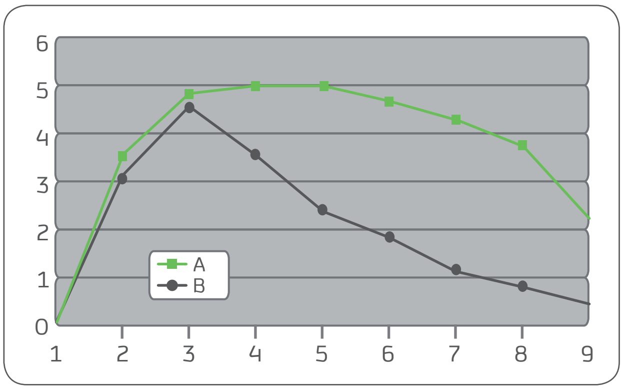
A sound understanding of emotions in network collaborations requires the study of emotion-dynamics in established groups. Emotions unfold over time, however, individuals are likely to differ dramatically in the time they need to recover from a negative emotion, for example, this can be seen in most network interactions, such as anger. There is neurological evidence that "time course modulation in affective responding, particularly for recovery, is one important component of what Prefrontal Cortex does" (Davidson, 1998).

Individual differences in emotional reactivity or affective style can be fruitfully broken down into more elementary constituents, such as threshold for reactivity, peak amplitude of response, rise time to peak and the recovery time. The two latter characteristics constitute the components of affective chronometry. The duration of an emotional episode can then further be defined as the amount of time between this onset point and the first moment the emotional experience is no longer felt (Verduyn, Van Mechelen & Tuerlinckx, 2009).

In order to classify emotions, different conceptual models of emotions usually adopt the following dimensions (Hascher, 2010):

- *Arousal* (deactivating/activating),
- *Valence* (negative/positive)
- *Intensity* (low-intense)
- *Duration* (short-long)
- *Frequency* of its occurrence (seldom-frequent);
- *Time dimension* (retrospective i.e., relief, actual i.e., enjoyment, prospective i.e., hope).

Figure 2. Affective chronometry of two different individuals in response to an emotionally arousing stimulus. Adopted by http://e-book.lib.sjtu.edu.cn/iupsys/Proc/stock1/spv1ch16.html

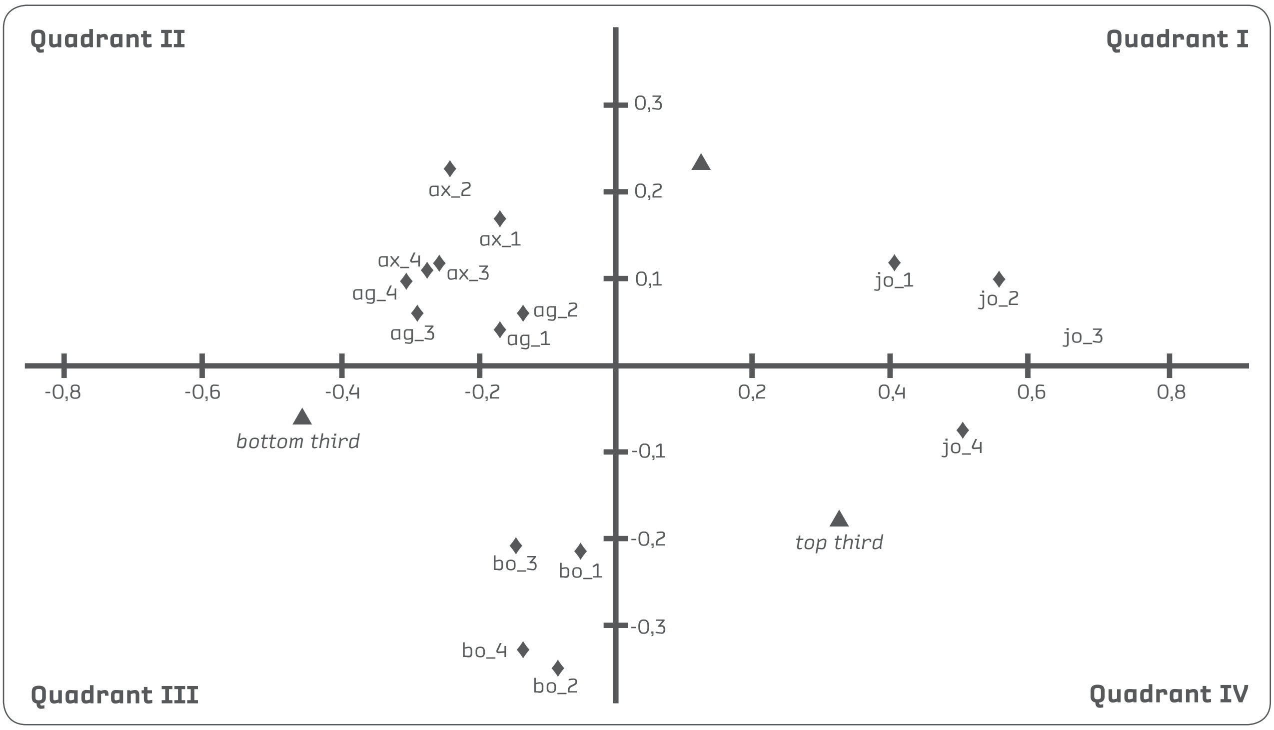


Pekrun (1992) supports that *time constraints for tasks* constitute another important variable that moderate learner's affective states. When time for task completion is limited (as in examinations), negative cognitive effects cannot sufficiently be compensated for by enhanced effort, thus rendering anxiety effects negatively. On the other hand, if cognitive processing impairment can be compensated for by extra hours of work (as in long-term preparation for an exam), the net effects of anxiety on achievement may well be positive.

Although quite few in number, studies that evaluate users' affective state with respect to *emotion duration (short-long)* and *time dimension (retrospective, actual, prospective)* can give us more precise views of emotions. For example, P. Verduyn and his colleagues (Verduyn, Van Mechelen, & Tuerlinckx, 2011) examined the extent to which covert intrapersonal actions (cognitions both related and unrelated to the emotion-eliciting stimulus) as well as overt interpersonal actions (social sharing) account for variability in emotion duration. According to their findings, one may also shorten the duration of an emotional episode by diverting attention away to topics unrelated to the emotional event, provided that the valence of the distracter is opposite to the valence of the emotion. Social sharing also prolongs episodes of joy and gratitude whereas shortening and prolongation effects of thoughts were also found for joy.

With respect to *time dimension (retrospective, actual, prospective)*, Kleine, et al. (2005) indicate that students do experience different levels of positive (joy) and negative (anger, anxiety, boredom) emotions according to their level of academic achievement in mathematics (bottom, middle, high), in short time periods (before, during, after the test).

Figure 2. Correspondence analysis for emotions experienced during a mathematics test. ♦= emotion (ag - anger, ax - anxiety, bo -boredom, jo - enjoyment). _1 = before the test; _2 and _3 = during the test; _4 = after the test. ▲ = achievement group. Adopted from Kleine, et al. (2005).



T. Hatcher has conducted several long-standing studies to test the development of wellbeing in school (e.g. changes in enjoyment at school during primary and secondary education, Hascher, 2010). According to her findings, there is a negative spiral of learning and emotion, which might be one important reason for insufficient learning outcomes and the high amount of inert knowledge developed during schooling. Learning enjoyment decreases over the years at school, and the decline seems to be caused by the characteristics of the organization of school learning, like a poor fit between students' interests and needs and the learning environment (Hascher, 2010).

Finally, time factors can also be considered during the affective feedback process, in which various heuristic policies are applied in response to user's emotions (Woolf, Burelson, & Arroyo, 2007). Shute (2006) is classifying instructional feedback according to type (explanation, hints, worked examples) and timing (immediately following an answer, after some elapsed time). One general recommendation is that immediate feedback helps low achieving students. Delayed feedback is suggested for high achieving students, especially for complex tasks.

DISCUSSION AND CONCLUSION

Although, CSCL researchers evaluate group activities and network systems that describe impact on the cognitive aspects of activities, almost no experimental research has been performed to evaluate the affective aspects of these group activities (Calvo, 2009). Just placing students in networked groups does not guarantee collaboration (Kreijns, Kirschner, & Jochems, 2003). Maintaining a level of student engagement in the tutoring process should be a priority. Enhancing students' attention and willingness to continue may imply sacrificing students' learning at times. If the long-term goal is to have students learn and 'stay' in a system, it may be important to sacrifice immediate learning by interleaving multimedia 'adventures,' for example, when observing signs of boredom or confusion to recover students' engagement with the system. (Woolf, 2007).

Our focus is on fortifying existing Learning Environments and ITS with the necessary emotion-aware strategies to address the affective states of the learner. The use of sensors to detect student's affective state may face obstacles (mostly financial but also spatial). However, the use of standard devices such as mouse-keyboard and PC camera to capture subjective, unconscious motor-behaviour patterns by testing contextual variables (correct/incorrect attempts, time in session, number of hits, etc., derive from log files (Arroyo, 2009).

Interventions include emotional scaffolds that encourage student's positive attitude towards learning and empathetic strategies that assure student's emotional safety and foster their meta-cognitive and meta-affective skills. We must develop effective production rules that preserve successful affective learning sequences, in line with educational design patterns. Feedback will be enriched by practices that have been tested and evaluated for years in Social-Emotional Learning (SEL) applications.

Walther (1992) argues that research has not taken into account the effects of the time needed to accumulate the socio-emotional cues necessary to develop their personal impressions of others. Time appears to be an important factor that positively affects development of an affective structure and, therefore, community building. If we take into consideration that even face-to-face groups need time for group forming and establishing an affective structure the 'time' we are talking about here, is- in fact- extra time needed due to the limitations of Network Computing. He suggests for the design of sociable CSCL environments aimed at providing non-task contexts that allow social, off-task communication (e.g. casual communication).

What the user-student really wants and feels in a specific time and space is appraised as valuable information that can lead into real personalised computers systems. Emotional scaffolding in CSCL has in fact led to significantly greater persistence and student engagement (Aist, 2002). Real and challenging collaborations need emotion awareness (detect and respond). And emotion consideration cannot be evaluated independently from the time factor.

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