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Challenges in the Development of Affective Collaborative Learning Environment with Artificial Peers

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Abstract **– Collaborative learning is a process that involves a group of peers collaborating with the aim to acquire new knowledge or skills. Collaborative learning environment enables such interactions by means of ICT. The paper focuses on affective collaborative learning environments, i.e., collaborative learning environments that are additionally aware of user's emotions and moods. Based on the analysis of existing research, a general architecture of an affective collaborative learning environment has been proposed in the paper and the main challenges for developing such an environment have been identified, namely, nonintrusive and safe detection of user's emotions, the adaptation of tutoring strategies, as well as modelling of artificial peers. This study can be considered the first step for the development of the collaborative learning environment that takes into account various affective aspects during the collaborative learning process.**

Keywords **– Affective computing, agent-based modelling, collaborative learning environment, tutoring adaptation.**

I. Introduction

Collaborative learning is a process that involves a group of people working together on a shared learning goal [1]. It has been proven by both scientific research and empirical observations that learning environment enhanced with peers facilitates the quality of study process and learning results. Some of the examples of collaboration include helping each other, doing learning activities together, competing or collaborating depending on what motivates the students in the group. These are the reasons why experienced teachers use various group-based learning methods to facilitate the learning process.

With the development of online communities and internet technologies, IT support for group learning has been advancing. In collaborative learning systems, groupmates bring different ideas and experiences to the group, working online to construct answers to questions and solutions to problems [2]. So far, the questions in the centre have been (1) how to form the groups to achieve the best combination of involved participants, considering the knowledge level as well as other personal factors, and (2) how to facilitate collaboration among participants [3].

Nevertheless, by combining the properties of online collaborative learning environments in general and intelligent tutoring systems, enhanced group learning environments can be developed. In such systems, group members are not necessarily all human but instead – intelligent agents acting as companions (or classmates) with speech, gestures, and emotions. Moreover, they can carry out pedagogical functions, thus supporting the work of the tutor.

Emotions (or *affects* – broad term for denoting emotions, moods, personalities and other related terms [4]) are a crucial part of learning; positive emotions increase students' ability to perceive information, improve memorizing, etc.; negative emotions, on the other hand, can mitigate the ability and motivation to learn. Thus, emotion recognition, student's emotion regulation and the system's adaptation to student's emotions are the key tasks in developing any learning environment. In general, in classroom settings, not only teachers but also classmates are able to recognise student's emotions; therefore, the development of collaborative learning environments requires methods for artificial peers to interact and react towards users' emotions and to interact among themselves.

Even though emotions in the learning process are recognised as an important factor and collaborative learning is considered a method facilitating learning, interaction, and communication, we still lack a learning environment combining both mentioned aspects. Therefore, the following research question "*What are the main reasons why affective (i.e., affect-aware) collaborative learning environments do not exist yet?*" has been addressed in this paper. This leads to the focus of this paper – challenges related to the development of affective collaborative learning environments. As a result, the general architecture of intelligent tutoring systems has been supplemented. Based on literature review, the main challenges, sub-challenges and the solution domains have been identified.

The structure of the paper is as follows: in Section II, it is elaborated in detail how emotions impact a collaborative learning environment. In Section III, the general architecture of a collaborative learning environment has been described based on the architecture of intelligent tutoring systems. In Section IV, the identified challenges are described. Finally, conclusions are given.

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II. State of Art in Affective Collaborative Learning Environments

Affective collaborative learning environments in this context combine the benefits of affective computing, intelligent tutoring systems as well as collaborative learning environments, thus having the following properties and functions:

- simulated artificial companions that carry out peer as well as pedagogical functions;
- awareness of user emotions and ability to express emotions through companions;
- choosing tutoring strategy and adapting it to user's emotions.

In the past decade, research efforts have been devoted to introducing adaptivity and intelligence in the context of computer-supported collaborative learning [5], [6]. Largely it is because teamwork, communication skills, and collaboration have been recognised as one of the most important 21st century skills in the modern society; the world is increasing in complexity and a single individual cannot complete many tasks alone [3].

In general, the introduction of adaptivity and intelligence in collaborative learning environments can improve the personalized support provided to students working in a group as well as facilitate learning of domain skills and development of collaboration skills. Regarding this issue, it is considered that approaches used in intelligent tutoring systems could facilitate the development of adaptive and intelligent collaborative learning environments. Current intelligent tutoring systems supporting one-to-many tutoring have limited capacity regarding tutoring adaptation to several students because ITSs traditionally have focused on approaches (e.g., curriculum sequencing, problem-solving support or feedback provision), which aim at helping individual student and not the group [1]. An adaptive, intelligent learning environment needs to select right pedagogical strategies at the right time based on student model in specific learning situations and in general in order to maximise deep learning and motivation while minimising training time and costs [3].

Development of such a collaborative learning environment becomes even more complex since adaptation is carried out not only to individual student but also to a whole group; therefore, new challenges appear that do not exist when the individualized learning process is supported. Since learning occurs in social situations and through interaction between students, specific cognitive, motivational and emotional factors are activated that can facilitate individuals' learning and collaboration within groups. The effectiveness of collaborative learning does not appear from simply putting people together. It requires systematic cognitive, motivational and emotional effort to achieve improved learning outcomes. Problems and disagreements appearing during the interaction can create not only a socio-emotionally unbalanced group climate but also endanger effective collaborative learning unless group members can regulate their emotional experiences and expression of their emotions [7]. Both negative and positive emotions experienced within the group emerge from multiple sources that can include a variety of factors, starting from personality differences to the dynamics and processes created within the collaborative group [8]. For example, if students are positively attached to a group, they are more likely to do their best to succeed in the learning activity; in turn, in a negative atmosphere, which appears, for example, if students do not get along well with their learning partners and display negative emotions towards them, group members may decrease their engagement in the learning activity [9].

Described examples show how problematic collaborative learning can be; all these aspects should be considered during the development of collaborative learning environment, which is aware of student's emotions and uses these emotions in the teaching process of a whole group.

To improve the efficiency of such environments, increasingly developing trend is systems in which student is presented by at least one companion agent [1], [3]. The agents can play different roles, such as a tutor who helps an online student learn specific concepts, a peer student who provides alternative perspectives, a teacher who guides a team through a complete learning path, a facilitator who maintains healthy social interaction among team members promoting positive emotional atmosphere, etc. [2].

Artificial companions compared to human companions present two main benefits: predictability in a sense that they will not just stop collaborate, and adaptability meaning that artificial agent can be tailored to the specific student. This, in turn, solves the issue of finding compatible students when forming a group. Small yet important practical benefit is off-line availability.

To unlock these benefits, it is crucial for artificial peers to be believable (i.e., perceived as if they act on their own). Believability is closely related to emotions – humans tend to perceive virtual assistants that have emotions as life-like companions [10].

When it comes to emotional capacities of existing artificial learning peers, they are very limited. Several existing collaborative learning systems can display encouragement or simple emotions [2] but, in general, affective capacities of companions in such systems are underdeveloped. While one might argue that in many cases an intelligent tutoring system does not need to be emotional but just needs to adapt to student's emotions, this does not apply to peer agents. Research shows that being in a group can lead to elevated affective states [11]. Such a state could bring several benefits for a collaborative system and a student working with it, but to achieve it, the system needs to be believable enough, which itself is a tremendous challenge.

In general, the development of affective collaborative learning environment that can provide an adaptive and intelligent support to a student is critical when the system aims at evolving various skills (e.g., social and emotional intelligence, coordination, interaction, communication and teamwork skills [12]) required in a modern world. While the system that uses artificial peers offers several significant benefits, implementation of such agents and their emotional capabilities is currently beyond state of the art. The creation of such a system forces to face a number of challenges (e.g., the adaptation to the student's emotions [13]), that are in detail identified and discussed in the further sections.

III. General Architecture of Affective Collaborative Learning Environment

To develop the general architecture for an affective collaborative learning environment, a traditional structure of intelligent tutoring systems is used as a basis. Essentially, the main difference between the traditional and collaborative learning architecture is a learning companion module, which in turn causes changes in pedagogical and interface module algorithms as well. The traditional structure of the intelligent tutoring system consists of four modules [14]:

- a student diagnosis module that collects and processes data about a student (his/her learning progress, problem-solving behaviour, psychological characteristics, learning style, etc.) and a student model that stores this data;
- a pedagogical module that is responsible for implementation of the tutoring process and a pedagogical model storing tutoring methods and strategies;
- a problem domain module that is able to generate and solve problems in the problem domain and a domain model storing knowledge what must be taught to the student;
- an interface module managing interaction between the system and the student through different devices.

A companion module is the fifth module in the structure that is needed to make the system collaborative. It is supplemented by a companion model that stores learning companion parameters (see Fig. 1). Companions not only carry out functions that are related to other modules but also perform their own actions in the environment. In its core, a newly introduced module is a human group simulation model. It has been suggested and proven by multiple studies (see, e.g., [15]) that the most effective human group modelling (not to confuse with population modelling) approach is agent-based modelling, which allows humans to be modelled at individual and individuals' interaction level. Since in this case learning companions communicate with student and must implement their own strategies, agent-based simulation is the most appropriate tool. This makes each learning companion an agent [16] – a type of program that consists of algorithms enabling making decisions.

The module interacts with other modules in the following way:

- the companion module uses a student diagnosis module to acquire information about student's personality and other affective states, which in turn is used to create learning companions with corresponding personalities. Companions also compare their own perception of student and the model that is produced by a student diagnosis module, thus updating the student model;
- companions implement pedagogical strategies selected by the pedagogical module, which means that the pedagogical module must contain algorithms allowing one to select an appropriate group mode, e.g., collaborative or competitive. Moreover, a research question arises from the perspective of agent implementation: if pedagogical decisions and actions are carried out by more than one agent (by a group of agents), how to share actions between agents? Partly this is answered by methods used by a paradigm called multi-agent systems, which for one thing develops methods and algorithms for resource and task sharing in a distributed system [16];
- companions have their interface, which directly relates to the communication module. The interface can consist either of embodied agents or a text chat, depending on the environment. The agents receive and send messages to the student via this interface;
- companions use both an expert module and a student diagnosis module to adapt to a student's knowledge level.

Based on this architecture as well as the literature analysis, three main challenges in the development of affective collaborative learning environments are identified, which are discussed in the next section.

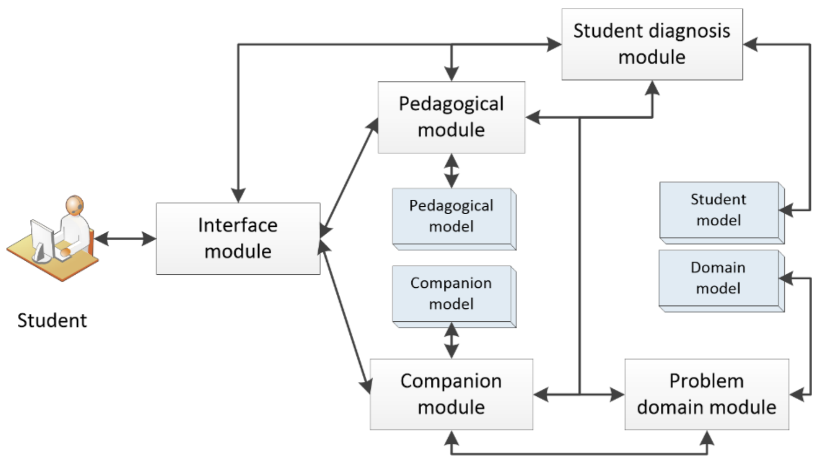

Fig. 1. The general architecture of affective collaborative learning environment.

IV. Challenges

It has been stated above that having a learning group offers multiple benefits; however, it is also a challenging task. The authors of the paper have identified three methodological and implementation issues as the most crucial:

- **Emotional state acquisition**. Emotion recognition has been one of the first focuses of affective computing, so a significant progress has been made in some directions: emotion recognition from camera, posture or voice [17]. Still, emotion recognition is a challenge that is not fully tackled yet. While there are no problems with acquiring emotion from camera when a person is sitting right in front of the computer, multiple challenges arise when (a) user is seen partially or from an unusual angle, (b) when several sensors (such as camera and log data) are giving contradicting cues or (c) when a person simply does not want to be observed and switches the camera off [18];
- **Adaptation to a student's emotional state**. Even if there were a method that allowed acquiring student's emotions in a sufficient and effective way, it would have no use if the system had no strategy on what to do with the acquired data next. For this reason, adaptation algorithms and methods are needed. Adaptation is not trivial since there are a variety of instructional factors (e.g., learning goals, standards relating to some curriculum, learning tasks, available tutoring components, errors and obstacles [19]) and student's parameters that influence learning process, including learner's static characteristics (like personality type, learning style, prior knowledge level, etc.) and dynamic characteristics, including emotional state [20].
- **Modelling of artificial peers**. The last challenge includes modelling and implementing learning companions. The believability of companions applies not only to visual resemblance to a human character (whether embodied or in chat communication) but also companion behaviour, especially emotion displays and emotion-related actions. Furthermore, the artificial peers need to communicate in order to pass emotions as well as share tasks, which means that they need to be well-balanced between choosing a strategy and believable interaction.

These challenges are further reviewed in detail in the subsections. General challenge classification as well as solutions and the corresponding research areas are displayed in Fig. 2.

A. Emotional State Acquisition

An integration of various sensors providing data about student's emotional state, for example, physiological sensors (e.g., skin conductivity sensor, heart rate sensor or electromyograph) or observational sensors (e.g., video cameras, eye trackers or microphones) improves the accuracy of emotion recognition. However, previous experience acquired during empirical evaluation of the developed emotionally intelligent tutoring system has shown that observations demonstrate that fear and negative attitude still exist regarding affect-aware technologies and not all students are open to the analysis of their emotional data, even if data is acquired using video cameras [13]. Therefore, other methods for the emotion identification, which do not influence a student in an intrusive way (e.g., analysis of interaction data or use of input devices), should be considered for the integration in learning environments.

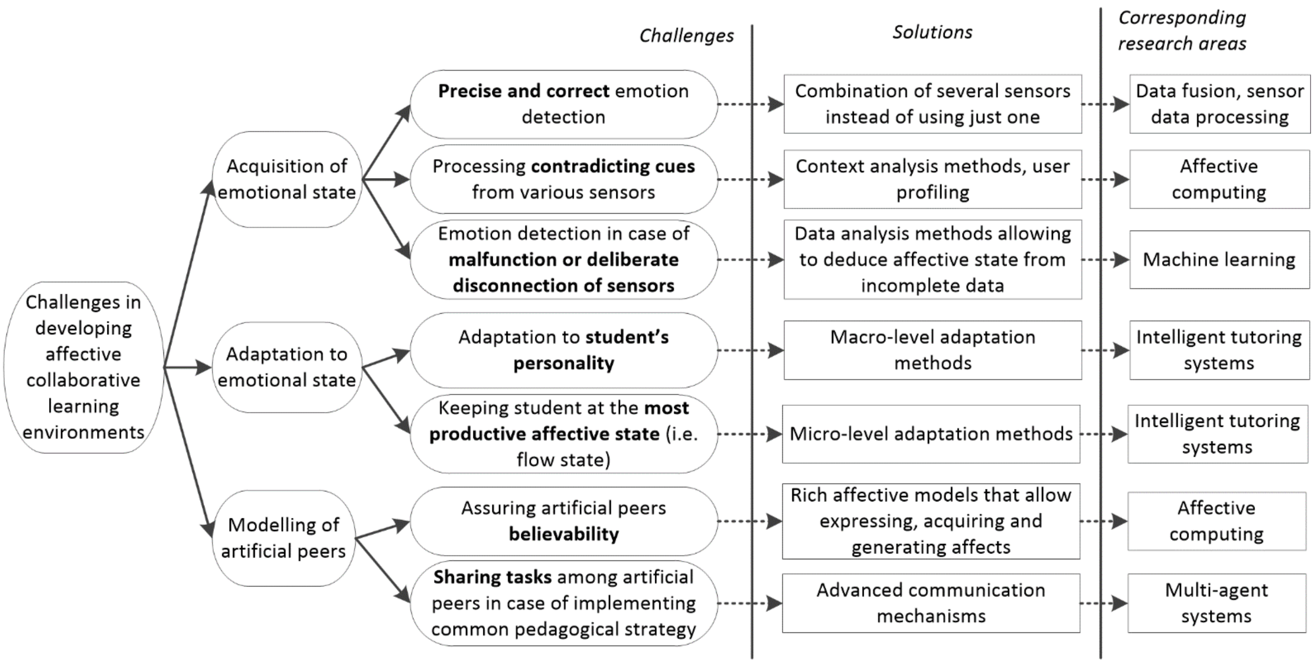

Fig. 2. Identified challenges, solutions and corresponding research areas.

Besides, many other reasons exist, which do not speak in favour of the use of sensors [21]. This can mainly be explained by the limited availability of sensors in real learning conditions (e.g., classroom settings). In the best-case scenario, computer classes or students' laptops are equipped with microphones and video cameras, not to mention various physiological sensors used in emotion detection and costs associated with the introduction of such high-level accuracy sensors in learning settings. In addition, an important reason is real-time data processing, which may require high computer performance or adequate data transfer speed [22]. Although it is believed that a sensor-free approach is a viable solution when it comes to transferring affective tutoring systems from laboratory conditions to the classrooms or students' homes, the crucial issue is the accuracy of emotion recognition, which decreases with the absence of sensors. Regarding this issue, additional research is required since current sensor-free approaches (e.g., analysis of log files registering student-system interaction) do not provide sufficient accuracy of emotion recognition [18] and thus can crucially decrease the efficiency of the adaptation of the system's behaviour and tutoring process.

Creation of the collaborative environment with virtual companions allows extending communication channels with a student and provides one more source for the emotional data acquisition – the communication between a student and companions can serve as a source of emotional data. It serves as an advantage regarding accuracy improvement of non-intrusive emotion detection. There has already been done some research on text analysis (see, e.g., [23]) with an aim to understand how people express emotions through text (both written language and transcriptions of oral communication). Another emotional data source can be usage analysis of input devices (e.g., mouse or keyboard). In the past years, several studies have been done in this direction (see e.g., [24]). Even though a current accuracy level of mouse/keyboard usage analysis is a bit above 60 % [25], the combination of aforementioned methods (analysis of text and input device usage, as well as student-system interaction) could lead to more accurate sensor-free emotion detection.

B. Adaptation to a Student's Emotional State

Modern intelligent tutoring systems are providing adaptation not only to learner's knowledge level, performance, learning style, learning goals, and interests but also to memory load limitations, behavioural, cognitive (learner's thinking, perceiving, remembering, or problem-solving strategies), affective, motivational, and other psychological states that change during the learning process [26]. Therefore, personalization of learning is a quite challenging task and there is no "one-size-fits-all" pedagogical strategy able to cover various students and their characteristics, particularly different emotional states [27].

Studies show that different emotional states impact learning process and outcomes in multiple ways. While positive emotions increase student's motivation, promote creativity and ability to adapt to different problems, negative emotions can prevent concentration, remembering, reasoning, etc. [28]. A well-motivated and concentrated student who is in the so-called flow state will achieve much better results. Based on the flow model (see Fig. 3), occurrence of other emotions like boredom or anxiety shows a mismatch between challenge (task difficulty level) and knowledge level; therefore, occurrence of such emotions can help identify, for example, knowledge gaps [29].

Student's personality and personality traits can provide information about the student's behavioural and psychological characteristics. Analysis of existing research related to the personality's influence on the learning/teaching process shows that the student's personality can be used to identify various factors that can, in turn, be used for the adaptation purposes. Examples for such factors are student's default mood that impacts tendency to particular emotions and their intensity [30], student's learning goals [31], student's intrinsic motivation to learn [32], student's learning style [33], and preferences for specific teaching methods [34].

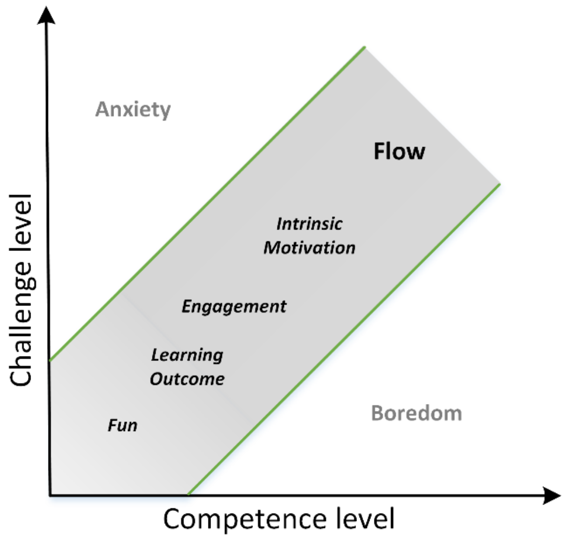

Fig. 3. Flow model (adapted from [29]).

Furthermore, a student's goal orientation, such as mastery orientation or performance orientation can be a crucial parameter affecting tutoring situation and interaction with a tutor or other students. Mastery orientation is characterised by persistence in the case of failure, the use of more complex learning strategies and the pursuit of challenging material and tasks. In turn, performance orientation is characterised by a tendency to quit earlier, withdraw from tasks (especially if failures are present) and seek less challenging material [35].

Provision of sophisticated personalization of learning requires the adaptation of tutoring at two levels [36]:

- at the macro level pedagogical strategies should be adapted to static student's characteristics (like personality type, learning style, an achievement goal, prior knowledge level, etc.);
- at the micro level – to student's dynamic parameters (e.g., learning progress, actions completed and especially student's emotional state).

Furthermore, the inclusion of mentioned student's parameters will lead to a more comprehensive student model that will allow a system to adapt its behaviour more appropriately in order to address the learner's needs by changing the pedagogical strategy. A pedagogical strategy that is better aligned with each student's needs is more likely to influence their learning gains in a positive way [3].

C. Modelling of Artificial Peers

There are two main issues to consider when modelling artificial peers: believability and task sharing.

Agent-based modelling offers a set of tools for developing a believable simulation of a group of peers, yet it does not specify anything about emotion elicitation and communication. It views the simulation model at two abstraction levels, likewise multi-agent systems, namely, at a micro and a macro level [16]. These levels can be considered a framework, but specific methods need to be integrated from affective computing research.

Micro-level includes single-agent behaviour. In this case, affective computing methods for emotional state elicitation, emotion expressions, and emotional state mapping on rational behaviour and reasoning should be considered. Macro-level views the system from a higher abstraction level and defines agent interactions. This means that methods enabling emotion communication and perception from other agents should be implemented.

Rich affective model is crucial for agents' believability; several such models have been developed. The most relevant to affective collaborative learning environments is ALMA – an agent model that is intended to teach a student and have an affective model that includes personality, mood, and emotions [37]. Similarly, WASABI is an agent that plays a card game and also has a multi-layer affective state [38]. When integrated into the learning environment, these models can provide a sufficient degree of believability at a micro-level.

A different situation is observed with group models. These models are much less researched from the psychological as well as affective computing perspective. While there are several developments that study the behaviour of the crowd (see e.g., [39]), much less work exists on emotions in smaller groups [40]. Thus, modelling of emotion communication mechanisms at large remains a challenge.

The second issue regarding the agent-based model is task (e.g., pedagogical strategy implementation) sharing. It has already been accented that agent-based modelling does not examine such methods; however, several methods from multi-agent systems can be used. Task sharing is a process through which agents coordinate and decide who performs which task [16]. It can be used to share pedagogical functions that need to be carried out by artificial peers.

V. Conclusion

The paper presents the state of the art and general architecture of the affective intelligent tutoring environment as well as discusses and classifies the main challenges in developing such an environment.

The task of developing such an environment is highly interdisciplinary – it includes combining tools, methods, and ideas from affective computing (including emotion simulation and emotion recognition), intelligent tutoring systems, agent-based modelling and multi-agent systems.

The main gain of developing such a system, however, is also considerable: combined benefits of group's positive influence from the collaborative learning perspective and carefully tailored strategy from the pedagogical perspective could enable even higher learning results.

Moreover, an affective intelligent tutoring environment is a well-suited tool for teaching soft skills, such as an ability to work in a group, which so far remains unexplored in the area of intelligent tutoring systems. While current collaborative learning environments can present an opportunity for learning such skills, they are still exposed to the human factor, which means that other participants might not be interested in teaching others to collaborate. The use of artificial agents, on the other hand, allows replaying the same scenarios, they do not get tired and more importantly, in the process of learning to communicate, real people do not get hurt. It becomes crucial when such systems are used for adolescents or kids.

The challenges that need to be tackled to implement such systems are not trivial. Yet from the research and discussion, it can be concluded that many usable methods exist in separate research areas (see Fig.2.); the overall challenge or "meta-challenge" includes integrating these methods. Considering the requirement and benefits for affective collaborative learning systems, bridging the gap between the need and the actual system is not in the far future.

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