Designing Affective Support to Foster Learning, Motivation and Attribution

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Abstract. Our work involves the design, implementation and evaluation of *Affective Learning Companions*, real-time computational agents that infer students' emotions and related states and leverage this knowledge to improve educational outcomes. In this paper, we focus on describing the affective support delivered by these learning companions. To date, unfortunately, there do not exist prescriptive theories on how to design the structure of affective support or how it should be tailored to suit individual student needs, even though these factors are critical in shaping learning and affect-related outcomes, making the design of affective support challenging. Our approach in addressing this challenge has been to involve human tutor experts in the affective support design process. Here, we present the wide range of affective scaffolding that we designed, which includes both verbal and non-verbal interventions, the stochastic algorithm for combining various affective interventions into complex messages aimed at fostering motivation, attribution and positive affect, and the evaluations we are currently conducting.

Keywords. affective support, learning companions, motivation, attribution

Introduction

Affect and related states such as motivation, empathy and attention play a fundamental role in influencing learning outcomes. For instance, learning fails to occur in the presence of negative affective states such as anxiety or anger [1], and is enhanced when empathy or support is present [2,3], e.g., interpersonal relationships between teachers and students increase student motivation (e.g., [4]). Despite the critical role of affect in the educational process, however, to date the research community has focused on the cognitive dimension, at the price of neglecting affect, as is pointed by key researchers [5,6]. Consequently, there do not yet exist prescriptive theories on how to design computational affective support or how it should be tailored to suit individual student needs, even though these factors are critical in shaping learning and affect-related outcomes.

Our work involves the design and evaluation of *Affective Learning Companions* (ALC), real-time computational agents that infer students' affective states and leverage this knowledge to increase student performance, affect and attitudes towards learning.

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Our key research question are: (1) how can a computational system determine, at any point in time, the affective state of a student and (2) provide appropriate tailored support that will improve the students' affective state and learning? In this paper, we focus on addressing the second question, and in particular, on the design of affective support delivered by ALC integrated into a computational learning environment.

One of the challenges with designing affective support is defining what this support should include, since as we point out above, there is a lack of fine-grained theories related to this issue. We do know that concepts related to affect such as self-efficacy play a critical role in influencing learning outcomes (e.g., [7,8,9]). In fact, emotional intelligence comprises self-motivation, empathy, self-awareness, impulse control and persistence [1]. Consequently, as is advocated in [5], we also argue that affective support should involve a wide range of scaffolding, spanning from empathetic responses, to attribution-based messages aimed at changing student feelings towards mathematics, to messages motivating students to shift their problem-solving strategy. To design this wide range of support, our approach has been to involve tutor experts in the feedback design process. We integrated our affective support into our test bed application, Wayang Outpost, a multi-media Intelligent Tutoring System (ITS) [10,11], thereby extending existing work by providing an ITS with a full spectrum of support aimed at fostering learning, positive affect, motivation and attribution.

We begin by describing some related work, and then present Wayang Outpost and its student model for assessing affect. We then describe the affective support we have integrated into Wayang, including the individual interventions and the stochastic algorithm for combining them into feedback messages. We conclude with an overview of the ongoing evaluations for evaluating this support.

1. Background and Related Work

Since a prerequisite to the provision of tailored affective support is affect recognition, there have been efforts in analyzing human (e.g., [12]) and computational (e.g., [13,14]) ability to infer affect during instructional situations. Here, however, we focus on related work pertaining to the design and delivery of feedback in general and affective support in particular.

Given that feedback plays a fundamental role in the educational process, the ITS community has been exploring how computational tutors can best provide it. To date, much of this work has focused on non-affect related factors (e.g., [15,16]). Recently, Shute [6] conducted a review of how various feedback-related attributes such as message complexity, timing and student expertise influence learning outcomes. As she points out, to date there is very little research on affective feedback and its role in shaping educational outcomes, and that there is a need to "systematically explore the affective components and outcome performance".

A number of researchers have begun investigating these avenues. Some of this work is based on human-to-human tutoring sessions. For instance, Porayska-Pomsta et al. [17] analyze such sessions to determine how human tutors diagnose student affect and the actions that tutors take as a result. Likewise, Lehman et al. [18] analyze affective states students experience during learning, as well as tutor responses to students actions during one-on-one sessions. Boyer et al. [19] investigate the balance between providing motivational and cognitive (e.g., hints on the domain) feedback during tutoring. Their findings highlight that in some instances, cognitive and motivational feedback are at odds with one another: feedback incorporating both aspects increases self-efficacy but decreases performance. We should point out that while studies on human-to-human tutoring provide an important foundation, translating the results into computational models is complicated by the lack of fine-grained details, on for instance, wording or adaptation to concrete situations not described in the analysis, and/or understanding of how the findings translate to computer-to-human tutoring.

There is also some work on integrating affective support into ITSs. For instance, Zakharov et al. [20] describe an emotionally-intelligent agent that generates empathetic responses during problem solving, e.g., the agent appears sad when the student makes poor progress. The evaluation shows students in general prefer the affective agent over the non-affective counterpart. Burleson and Picard [21] describe a learning companion that mirrors students' affective states through non-verbal gestures and provides affect-related verbal support, corresponding to informing students about Dweck's "the mind is like a muscle" message [22]. The evaluation shows that tailored sensor-driven affective support influences students' motivation and attitudes towards the tutoring application, and that this effect is mediated by gender.

2. Wayang Outpost

The test bed application for our research is Wayang Outpost, a multimedia ITS that trains students to solve challenging geometry problems of the type that commonly appear on standardized tests [10,11]. To answer problems in the Wayang interface, students choose the solution from a list of multiple choice options (typically four or five, see Fig. 1A). Wayang's original form of support corresponded to the following two types. First, while students solve a problem, they could ask Wayang for hints. The hints contained information on geometry rules needed to solve the target problem; for a given problem, the hints would become progressively more specific until a bottom-out hint was reached. Second, between problems, i.e., after a student finished a problem and before she started a new one, Wayang presented progress reports that informed students about the accuracy of their problem solving (see Fig. 1B). The progress reports are designed to reify to students their productive and unproductive behaviours, and inform them about the consequences of their actions on their progress. We evaluated the utility of this approach [10], and found that compared to students who did not see progress reports, students who did see them learned better, had higher learning orientation, and attributed more human-like characteristics to the Wayang tutor.

We have been working on extending the range of feedback offered by Wayang to include a rich array of affect-based support. To deliver this new support, we decided to integrate learning companion agents into Wayang, who are designed to act like peers that care about a student's progress, and offer support if he becomes frustrated or begins to lose interest. The underlying motivation for including peer-based companions instead of more traditional tutors is rooted in the extensive literature on the benefits of peer-to-peer tutoring (for an overview, see [23]). To design the companions, we collaborated with a cognitive psychology researcher, who provided us with concrete feedback on ways to make the characters more believable. Currently, we have two companions designed,

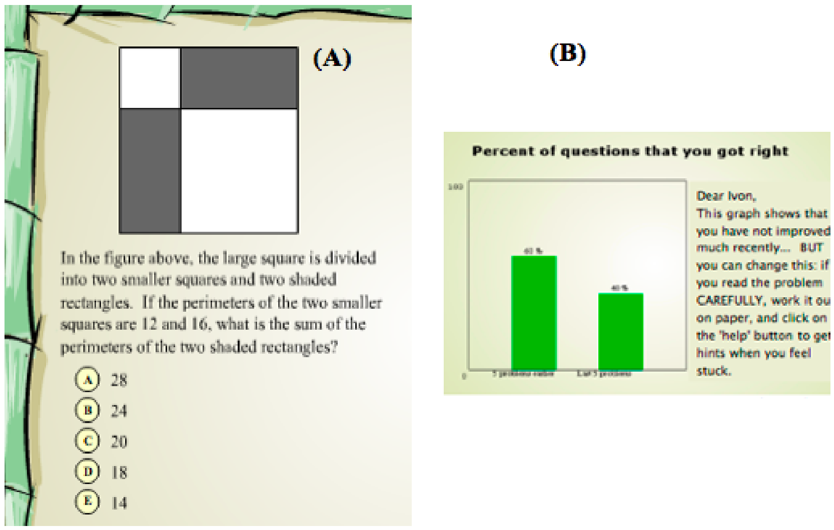

Figure 1. Wayang Problem-Solving Interface (A) and Wayang Progress Report (B)

Figure 2. Wayang Learning Companions, Jane and Jake

Jane and Jake (See Fig. 2), because we are interested in exploring how the gender of the companion influences the impact of affective support. Since we wanted the affective support to be tailored to students' needs, our first step has been to develop a student model capable of assessing students' affective states, that we now describe.

2.1. Inferring Students' Affect: the Wayang Student Models

Wayang includes two student models: (1) a simple effort model that is used to assess the degree of effort a student invests to generate a problem solution, and is based on time per action (i.e., if a student invests very little time between actions, this implies guessing and hint-abuse); (2) an affect model that corresponds to a linear regression model that Wayang uses to predict a student's current emotional state.

The affect student model, which we described in [11], is derived from data obtained through two evaluations we conducted in the fall of 2008 involving 38 high school students and 29 undergraduate students, respectively. Each evaluation involved students interacting with Wayang as part of their regular math class for 4-5 days. To obtain information on how students were actually feeling as they interacted with Wayang, we had Wayang prompt students on a set of four bipolar emotional axes, that define a total of 8 emotions. These four axes included: a confidence/anxiety scale, an interest/boredom scale, an excitement/lack of excitement scale, and a frustration/lack of frustration scale. During the study, we also used a set of sensors to capture students' physiological responses, including a pressure mouse, posture chair, skin conductance bracelet, and webcam supplemented with software for inferring affective states from facial features. All interface actions in Wayang and sensor data were logged.

To build the affect student model, we first identified a set of variables that we believed could be predictors of emotions, including (1) variables related to students' interface actions, such as number of hints accessed (referred to as 'tutor context' variables below); (2) variables related to the sensors, such as 'sit forward' events inferred from the posture chair (referred to as 'sensor variables' below). We then relied on stepwise linear regression to identify which variables were good predictors of each type of emotion we captured, with a student's self-reported emotion as the dependent variable, and the tutor context and sensor variables as the independent variables. We found that a combination of 'tutor context' and sensor variables resulted in the most accurate model for predicting student emotions (for details, see [11]).

3. Wayang's Affective Interventions

We now present the affective interventions that Wayang's learning companions deliver; ultimately, these will be tailored according to the student models described in Section 2.1. As we already mentioned, the design of affective support is challenging because there do not exist prescriptive theories on how to design such support or how it should be tailored to suit individual student needs. To address this challenge, our approach has been to involve teachers and scientists in the intervention design process, as well as to draw as much as possible from related work. In particular, the character messages were created in collaboration with several experts from the *Center for Applied Special Technology* (CAST) institute, which is a research and development organization that works to expand learning opportunities through universal design for learning (http://www.cast.org/). The experts included two research scientists both with doctorate degrees in education, who specialize in the role of emotions in the educational process in general, and addressing emotions during mathematics instruction in particular.

We met with the CAST specialists several times during the intervention design process, as follows (1) the CAST experts provided the initial intervention design and wording; (2) the first author then categorized these interventions according to type of intervention (e.g., empathetic, attribution, effort-affirmation), and also refined them (e.g., shortened them), relying on the related work as much as possible during this process (e.g., [24]); (3) the interventions were then sent back to the CAST team, who approved the changes, making revisions as necessary. We now present the set of affective interventions that were the product of this process.

3.1. Verbal and Non-Verbal Interventions Generated during Problem Solving

As we pointed out above, emotional intelligence involves factors such as self-motivation, empathy, self-awareness, impulse control and persistence [Goleman 1995]. Given that we want our learning companions to both appear emotionally intelligent and support the emotional intelligence of our learners, we have designed a wide range of affective support that incorporates empathy, attribution, strategy and effort affirmation. Wayang's learning companions deliver this support *while* a student solves a problem. The support includes both verbal and non-verbal scaffolding.

The *non-verbal* affective support corresponds to having Wayang's learning companions mimic through their behaviors whatever the student is feeling, which is a form of an empathetic response. For instance, one non-verbal intervention corresponds to having the learning companion appear excited in response to student excitement (see Fig. 2, right). Behavioral mimicry is a form of empathy that is prevalent in social interactions (e.g., [25]), here we are exploiting that property to foster social relationships between the student and learning companion.

The *verbal* affective support corresponds to a variety of messages that are verbally expressed by Wayang's learning companions. Note that these messages are designed to appear as if coming from a peer, instead of a tutor, who is solving the problems with the student in Wayang. We now describe the various types of verbal interventions that we have embedded in Wayang.

3.1.1. Empathetic Interventions

The CAST experts suggested that it is particularly important is to address students' negative emotions during verbal empathetic responses, because such emotions interfere with learning. Consequently, the *empathetic* interventions are expressed by the learning companions to acknowledge and/or support students' frustration and/or anxiety, with the hope of alleviating these negative feelings. If a student is frustrated and/or anxious, but it is not clear which, then the learning companion responds empathetically to address both emotions (e.g., *'I often get discouraged when struggling with a math problem"*). If the student is only anxious, then the empathetic response is geared at addressing anxiety (e.g., *"You know ... sometimes I get embarrassed when I get the answer wrong"*); likewise for frustration (e.g., *"Don't you sometimes feel frustrated with math problem solving? I do"*).

3.1.2. Attribution Interventions

According to attribution theory, students don't feel motivated to learn due to their attributions, i.e., beliefs, of why they succeed or fail at tasks (Weiner, 1986). Attribution training involves changing a student's beliefs in the causes of his or her own failures and successes to promote future motivation for achievement, and can have an significant impact on learning attitudes [26]. We have the following types of *attribution* interventions:

- The *general attribution* interventions are generated to encourage students to change their attitudes and feelings about math and learning in general (e.g., *"I found out that people have myths about math, like that only some people are good at math. The truth is that we can all be successful in math if we give it a try"*)

- The *effort attribution* interventions are generated when students are investing effort during problem solving but are struggling, and are designed to help students realize that this is a necessary by-product of learning (e.g., *"Keep in mind that when we are struggling with a new skill we are learning and becoming smarter!"*)
- The *no-effort attribution* interventions are generated when students are not investing effort when problem solving, and are designed to help them realize that effort is necessary in order to learn (e.g., *"We will learn new skills only if we are persistent. If we are very stuck, let's call the teacher, or ask for a hint from Wayang!"*).
- The *incorrect attribution* interventions are generated to motivate students after they get an incorrect response, by changing the way they think about errors (e.g., *"When we realize we don't know why that was not the right answer, it helps us understand better what we need to practice"*).

3.1.3. Effort-Affirmation Interventions

The *effort-affirmation* interventions acknowledge when students are (or are not) investing effort during problem solving. In contrast to the *effort-attribution* interventions presented above, which aim to change students' attitude towards effort during problem solving, the effort-affirmation interventions acknowledge effort or lack of with respect to a student's problem solving entry. By having the learning companion affirm effort (or lack of), the hope is to both build a more realistic social bond between the companion and the student and to motivate the student. The effort-affirmation interventions include the following:

- The *correct no-effort* interventions are generated after a student invests no effort and gets the answer to a problem right, to acknowledge that the problem given to the student was too easy for them (e.g., *"That was too easy for you. Let's hope the next one is more challenging so that we can learn something"*).
- The *correct effort affirmation* interventions are generated after a student invests effort and gets the answer to a problem right to acknowledge the student's effort (e.g., *"Good job! See how taking your time to work through these questions can make you get the right answer?"*).

3.1.4. Strategic Interventions

The strategic interventions aim to motivate students to reflect on their problem-solving strategies, and to foster motivation for problem solving as a result, as follows:

- the *incorrect strategic* interventions are generated when students are not succeeding at getting correct answers during problem solving, and are designed to motivate students to change their general problem-solving strategy, i.e., think about why they are not succeeding (e.g., *"Are we using a correct strategy to solve this? What are the different steps we have to carry out to solve this one?"*).
- the *correct strategic* interventions are generated when students are succeeding at getting correct answers during problem solving, and are designed to encourage students to think about their problem solving strategy, i.e., to consider why they are succeeding (e.g., *"We are making progress. Can you think of what we have learned in the last 5 problems"*).

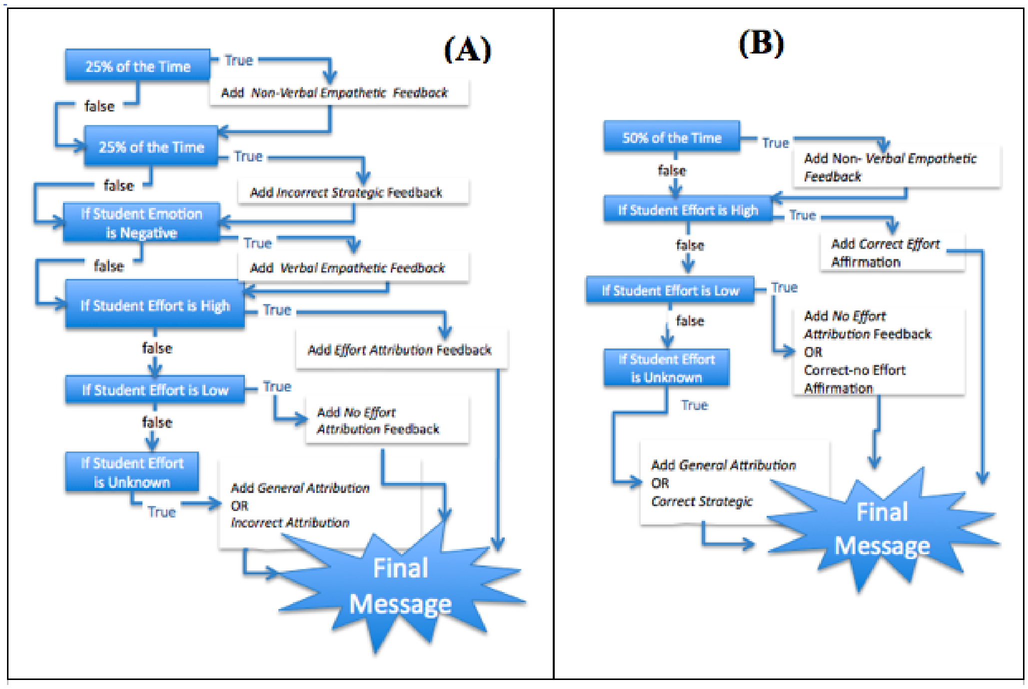

Figure 3. Wayang algorithms for integrating affective feedback presented in Section 3 into overall response: (A) algorithm used when student answer is incorrect; (B) algorithm used when student answer is correct.

4. Algorithms for Integrating Affective Interventions

Given the above set of various types of interventions, a question relates to how these should be presented to a student. While an option is to present each intervention individually, another is to combine the various types of interventions into an overall response. The advantage of doing the latter is that the integration of verbal and non-verbal feedback affords a more complex and potentially believable impression of the learning companion delivering the message. The disadvantage, however, is that the overall message length increases and there is a higher potential for repetition. We are experimenting with both approaches: (1) generating the interventions individually, according to a stochastic algorithm to increase variability, (2) combining the interventions into an overall message. The latter is accomplished by two algorithms we have designed, used (1) when a student's answer is incorrect (see Fig. 3A); (2) when a student's answer is correct (see Fig. 3B). The algorithms take into account student effort and/or affect to produce an overall message consisting of empathetic, attribution, strategic and effort-affirmation components, as appropriate. The algorithms include some stochastic properties, which are embedded to introduce variability in the learning companion's affective behaviors and so increase its realism.

To illustrate the algorithm output, let's suppose a student generates an incorrect answer really fast (indicating no effort); the student is frustrated. Intervention generated according to the above algorithm is as follows:

Character looks frustrated for a few seconds.	(Non-verbal Empathetic)
Don't you sometimes feel frustrated with problem solving? I do.	(Verbal Empathetic)
However,	(Connector)
we will learn only if we are persistent. If we are very stuck, let's call the teacher, or ask for help..	(No-Effort Attribution)

Now the student again generates an incorrect answer, but the effort is not clear and the student is anxious. Intervention generated according to the above algorithm is:

You know ... sometimes I get embarrassed when I get the wrong answer...	(Verbal Empathetic)
But	(Connector)
I think it is important to have an open mind and the belief that one can do math.	(General Attribution)

To refine the approach for generating interventions (e.g., individual messages vs. combined messages), we are currently piloting the various options.

5. Planned Evaluations and Future Work

Above we described the affective support we have designed and embedded in Wayang Outpost. This support includes both verbal and non-verbal interventions, which may be combined via stochastic algorithms we presented in Section 4 into complex messages aimed at fostering motivation, attribution and positive affect. Our next step is to evaluate the interventions. A general challenge is at what level to assess the affective support. One can take a broad approach and assess the impact of the interventions as a whole, without controlling for the impact of the individual components (e.g., visual vs. verbal feedback). An alternative is to conduct ablation studies, where we evaluate, for instance, the impact of each type of intervention. For the time being, we have chosen the former option, because we want to begin by exploring whether affective support has an impact in general before we tease apart the factors contributing to this impact (if any).

We are currently in the process of conducting a series of evaluations with Wayang, which include validation of its user models with new populations, and piloting of the interventions in preparation for the evaluation of the affective support, which will take place this spring with a series of high schools. In this study, all students will interact with Wayang over a series of sessions (typically 4-5) and all students will be asked to self report on their emotions at fixed time intervals (the prompt to do so appears after a student solves a problem and before she starts a new one to minimize interruption). To evaluate the impact of Wayang's affective support, our study includes three conditions: [1] students receive none of the above-described interventions (control condition); [2] students receive all of the above-described interventions but these are generated randomly instead of according to Wayang's student models (random feedback condition); [3] students are provided interventions and tailored based on their self-reported emotional state and/or effort invested. Our hypothesis is that the tailored affective support will be most effective in terms of learning and affect-related outcomes.

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