Developing Empirically Based Student Personality Profiles for Affective Feedback Models

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Abstract. The impact of affect on learning has been the subject of increasing attention. Because of the differential effects of students' affective states on learning outcomes, there is a growing recognition of the important role that intelligent tutoring systems can play in providing affective feedback to students. Although we are only beginning to understand the complex interactions between affect, feedback, and learning, it is evident that affective interventions can both positively and negatively influence learning experiences. To investigate how student personality traits can be used to predict responses to affective feedback, this paper presents an analysis of a large student affect corpus collected from three separate studies. Student personality profiles augmented with goal orientation and empathetic tendency information were analyzed with respect to affect state transitions. The results indicate that student personality profiles can serve as a powerful tool for informing affective feedback models.

Keywords: Affect, Affective Computing, Pedagogical Agents

1 Introduction

Affect has begun to play an increasingly important role in intelligent tutoring systems. The intelligent tutoring community has seen the emergence of work on affective student modeling [1], characterizing student emotional experiences [2,3], detecting frustration and stress [4,5], detecting student motivation [6], and diagnosing and adapting to student self-efficacy [7]. All of this work seeks to increase the fidelity with which affective and motivational processes are understood and utilized in intelligent tutoring systems in an effort to increase the effectiveness of tutorial interactions and, ultimately, learning.

This level of emphasis on affect is not surprising given the effects it has been shown to have on learning outcomes. Student affective states impact problem-solving strategies, the level of engagement exhibited by the student, and the degree to which he or she is motivated to continue with the learning process [8,9,10]. All of these factors have the potential to impact both how students learn immediately and their learning behaviors in the future. Consequently, developing techniques for keeping students in an affective state that is conducive to learning has been a focus of recent work [11,12,13,14].

However, while much work has targeted the development of optimal techniques for supporting student affect, the nature of the problem introduces a significant degree of uncertainty. In human-human social interaction it is often difficult to determine how best to respond to an individual's affective states. The problem is significantly more challenging for computational systems: they must first be able to correctly recognize student affective states and then decide how best to respond. Systems may frequently encounter situations in which they are uncertain about how to provide affective support and what the effects of a possible intervention may be.

Previous work [15] has indicated that poorly selected feedback mechanisms can have severe negative consequences for student affective states. In some cases the possibility of these negative consequences introduces such a risk that it is preferable to avoid giving any affective feedback. While this work has shed light on measures of risk and utility when considering affective intervention, systems should also be able to weigh an estimated confidence in the success of a particular feedback strategy against the risk associated with that strategy to make an informed decision on how to proceed.

In this paper we investigate the role of student personality, including goal orientation and empathetic tendencies, in estimating confidence in the benefits of an affective intervention strategy. We derive personality profiles categorizing students who tend to experience positive benefits or negative consequences of affect feedback from a corpus of student affect data spanning three user studies with a narrative-centered learning environment, CRYSTAL ISLAND. These personality profiles are then used to train machine-learned prediction models to determine confidence estimates for the expected benefit of a candidate affective intervention.

2 Background

A broad range of techniques have been developed to provide appropriate affective support. Some of these techniques are based on analyses of human-tutor responses to affect [12], while others are based on theoretical models of how to improve student performance by valuing effort over success [16]. Other work has focused on responding to specific student emotions using empathetic or task-based feedback strategies [15]. While many of these strategies have been shown to be beneficial in supporting student affect, they often do not consider specific student needs. Previous findings have suggested that a student's individual personality characteristics can strongly impact which affective states are most beneficial for the student [11] and how the student experiences and transitions from these states [17].

With these findings in mind, we seek to develop personality profiles to predict how students will respond to affective feedback and determine how this information can be utilized to better inform affective feedback models. We consider three distinct measures of student characteristics: personality, goal orientation and empathetic tendencies. These three constructs are expected to have a particular influence on the student's experience of narrative and learning emotions associated with the interactive environment as well as their ability to internalize and respond to agents' attempts to provide beneficial affective feedback.

Personality is an individual's disposition over a long duration of time, which can be distinguished from emotions or moods which are more limited in their duration [18]. The Big 5 Personality Questionnaire [19] decomposes personality into five primary categories: openness, conscientiousness, extraversion, agreeableness and neuroticism. Of particular interest among these are openness, conscientiousness and neuroticism, as these characteristics are likely to impact emotion and learning. Additionally, because information on affective states is often obtained through self-report, we expect to find individuals who score high on openness will display genuine emotions, while others may limit themselves to what they feel comfortable reporting.

Goal orientation reflects a student's primary objective when engaged in learning activities. Students may either view learning in relation to performance or mastery [20]. A performance approach would result in a student wishing to prove her competence and achieve better results than other students. A student with a mastery approach, however, views learning as an attempt to acquire knowledge or a skill, regardless of how her ability compares to others. In addition to these categories, students may have avoidance strategies in relation to their goals. For example, students with a performance-avoidance approach would simply try to not overtly fail, rather than try to top their fellow student. We expect that these students will differ in their tendency to stay negatively or positively focused especially in response to agent feedback.

Empathetic tendencies refer to an individual's responses to the situational and affective states of others [21]. These tendencies can be measured using an interpersonal reactivity index [22], which includes four subscales: fantasy, perspective taking, empathetic concern and personal distress. Fantasy refers to the tendency to identify with fictional characters such as virtual agents, or characters in books and movies. Perspective taking is an individual's capacity to see situations from the perspective of another individual. Empathetic concern is a tendency to exhibit compassionate emotions towards those in negative situations, while personal distress refers to feelings of stress and anxiety over the misfortunes of others. These traits may directly impact the student's perception of the characters and events in a learning environment and how they respond to agents' efforts to provide affective support.

3 The CRYSTAL ISLAND Environment

The affect corpus utilized in this analysis was obtained from studies conducted in a narrative-centered inquiry-based learning environment, CRYSTAL ISLAND (Figure 1). This environment is being created in the domains of microbiology and genetics for middle school students. It features a science mystery set on a recently discovered volcanic island where a research station has been established to study the unique flora and fauna. The user plays the protagonist, Alex, who is attempting to discover the source of an unidentified infectious disease at the research station. As members of the research team fall ill, it is her task to discover the cause and the specific source of the outbreak. She is free to explore the world and interact with other characters while forming questions, generating hypothesis, collecting data, and testing her hypotheses.

Figure 1. The user, Alex, with Jin, the camp nurse, on CRYSTAL ISLAND

She can pick up and manipulate objects, and she can talk with characters to gather clues about the source of the disease. In the course of her adventure she must gather enough evidence to correctly identify the type and source of the disease that has infected the camp members.

4 Method

To empirically investigate the differential responses of students in specific affective states, we consider cumulative data from three studies of students interacting with affect-sensitive virtual agents. These agents were developed to respond to student emotion and encourage positive student affect within the learning environment through three distinct feedback strategies: (1) task-based feedback, (2) parallel empathetic statements, (3) reactive empathetic statements or by providing no feedback. Task-based feedback strategies focused on directing students towards information that would aid in improving or maintaining their emotional state (e.g.,"You may want to consider reading a book on pathogens. You can find a good book in the lab"). This strategy aims to aid both students who are struggling with environmental tasks and those lacking the necessary content knowledge without attempting to distinguish between the two. Parallel empathetic statements demonstrate an agent's understanding of the emotional situation and reflect the affective state of the student (e.g.,"I know! It's very frustrating not knowing what is causing the illness!"). In contrast, reactive empathetic statements focus on the emotional needs of the student and will try to motivate a more positive affective state (e.g.,"I know this is a tough problem, but if you keep working at it, I'm sure you'll get to an answer soon"). Each type of feedback is limited to at most three sentences and directly acknowledges the emotional state reported by the student. Additional details on response generation may be found in [14].

Affect feedback models were iteratively developed over the course of three studies to improve the ability of the virtual agents to provide beneficial affective support. An affect corpus was obtained by aggregating data collected in these three studies and includes data from a total of 115 college students who interacted with one of the three models of agent behavior within the CRYSTAL ISLAND environment. Among these students, 89 were male and 26 were female. Ages ranged from 19 to 60 ($M = 24.63$, $SD = 4.93$). Demographics included 37.4% White, 47.8% Asian or Indian, and 14.8% Other (including African American, Hispanic, Other and Non-Response).

Participants entered the experiment room where they completed informed consent documentation and were seated in front of a laptop computer. They were then given an overview of the experiment agenda, and they completed the pre-experiment questionnaires including the demographics survey, the interpersonal reactivity index survey[22], the goal orientation survey [20], and the personality questionnaire [19].

Participants were then instructed to review CRYSTAL ISLAND instruction materials. These materials consisted of the backstory and task description, character overviews and a map of the island, the control sheet, and definition sheet of the self-report emotions. Participants were then further briefed on the controls via a presentation explaining each control in detail. Participants maintained access to the materials, including the definition sheet of the self-report emotions, throughout their interaction. Participants were given thirty-five minutes to solve the mystery.

When subjects decided to interact with the agents, the following schema was used to direct subject-character interactions and virtual character feedback:

1. The agent queries the subject for a self-reported affective state ($Report_1$) by asking the question, “Hi Alex, how are you feeling?” The subject may respond by selecting one of the available emotions (*anger, anxiety, boredom, curiosity, confusion, delight, excitement, flow, frustration*).

2. The agent then responds to the subject’s reported affective state with a randomized feedback response. Responses varied between parallel and reactive empathetic statements, task-based feedback or no intervention. The relative frequency of these feedback strategies varied between studies but is not the focus of this analysis.

3. If the student received a feedback response, a follow-up dialog box is then presented to the subject asking her to respond with the prompt, “… and you respond.” The subject is able to choose from four Likert-scaled responses designed to evaluate the appropriateness and effectiveness of the virtual character's response. Subjects can issue responses ranging from (1) “That does not help me at all,” to (4) “Thanks, that helped a lot!”

4. The agent responds with a one-word quip (e.g., “Thanks,” or “Great!”) directed towards the subject’s evaluation response (Step 3, when executed).

5. At the conclusion of the interaction, the agent again asks the subject how she feels. The subject is presented a dialog box similar to the one described in Step 1 without the character greeting. Here, the character prompts the subject with, “How are you feeling now?” and the student selects from the same set of emotions ($Report_2$).

5 Personality-Informed Affect Feedback

It was hypothesized that individual student traits can provide insight into whether students are likely to experience positive or negative affect transitions after experiencing specific types of affective interventions. Therefore, the first step in the analysis was to classify transitions as positive or negative based on their reported affective state after receiving feedback ($Report_2$). This was accomplished by considering emotions to be positive or negative based on their valence. For instance, curiosity is a positive emotional state, while boredom is a negative state. However, this classification did not reflect findings on the sometimes positive nature of the state of confusion which was therefore considered to be a neutral state. Using this framework, transitions were labeled as positive if subjects remained in or transitioned to a more positive affective state ($Report_2 \geq Report_1$). Similarly transitions were labeled as negative if subjects remained in a negative state or transitioned into a state that was more negative than they had experienced prior to the intervention. Using this framework, approximately 67.8% (n=716) transitions were labeled as positive, while the remaining 32.2% (n=340) were labeled as negative.

5.1 Personality Profiles

We first sought to examine whether or not there existed a personality profile for students who tended to experience positive or negative transitions. Exploratory t-tests compared the personality characteristics associated with positive and negative affective transitions. These tests were run on each component of the subscales for personality, empathetic tendencies and goal orientation. Results indicated that there were many student characteristics that contributed to a personality profile for positive and negative transitions (Table 1). For instance students who experience positive transitions tend to be more agreeable but also less open than students who experience negative transitions. These students also report experiencing less personal distress and greater ability to take the perspective of others. Finally, students experiencing positive transitions are more likely to have a performance avoidance approach to learning.

These results suggest interesting relationships between students' susceptibility to feedback and how they transition in response to it. For example, agreeableness and perspective taking are both associated with the ability to relate well with and consider the opinions of others. In the case of affective intervention, these students may be more willing to consider and internalize the helpful feedback of the virtual characters and consequently experience positive affective transitions. Alternatively, students who report experiencing higher personal distress may be more likely to remain in negative emotions associated with the ill characters of the island and are less likely to be consoled by the characters' interventions.

5.2 Emotion-Specific Personality Profiles

We next considered the possibility that these personality profiles may vary when transitioning from specific emotions. Therefore we conducted the same analyses on

Table 1. Trait tendencies. +/- indicate the direction of the trend, while * indicate a significance of $p < 0.05$ in exploratory t-tests.

	Overall				
	Neuroticism	-	*	Personal Distress	-
*	Agreeableness	+		Perspective Taking	+
*	Openness	+	*	Performance Avoidance	+
*	Empathetic Concern	+			
	Emotion Specific				
	Anger			**Anxiety**	
	Mastery Approach	-		Performance Approach	+
	Perspective Taking	-			
*	Agreeableness	-		**Confusion**	
				Performance Avoidance	+
	Boredom			Fantasy	-
*	Conscientiousness	+	*	Agreeableness	+
*	Agreeableness	+			
				Curiosity	
	Excitement		*	Perspective Taking	+
*	Perspective Taking	+	*	Openness	-
*	Agreeableness	+			
				Flow	
	Frustration		*	Mastery Approach	-
	Performance Avoidance	+		Performance Approach	-
	Fantasy	+	*	Fantasy	+
*	Extraversion	-		Empathetic Concern	+
	Neuroticism	+	*	Neuroticism	-

transitions from specific emotions. This analysis yielded many of the same traits reported in the overall personality profile, but also showed several emotional states that had specific personality profiles (Table 1). For instance, the trend for students experiencing positive transitions to be more agreeable was true when students reported an initial emotional state of *boredom, confusion***,** or *excitement.* However, the opposite trend was found for students who reported *anger.* In this case, students who experienced negative transitions scored much higher on the agreeable subscale than students experiencing negative transitions. This is an interesting anomaly and one that seems to contradict the typical characteristics associated with agreeableness, suggesting that there may be something unique about the emotional state of *anger* that warrants further investigation. Alternatively, the expected trends were found for students with high perspective taking, who were likely to experience positive transitions from emotions such as *curiosity* and *excitement*.

Additional characteristics outside the general profiles were found to be indicative of differential responses in specific emotional states as well. For instance, negative transitions from *frustration* were experienced by highly extraverted students. Meanwhile, conscientious students experiencing *boredom* appeared to be more susceptible to characters' attempts to reengage them and had a stronger tendency to experience positive transitions. Additional results suggest that some students responded particularly negatively to feedback when in a positive state. For example, mastery-approach students experiencing *flow* tended to experience negative transitions as did open students experiencing *curiosity*. This result is particularly interesting since in both of these cases, the students are experiencing positive emotional states that are expected to be particularly salient for their individual traits. It may be the case that an interruption of this positive or perhaps optimal state is responsible for this negative transition.

5.3 Models of Affective Response

The ultimate goal of this line of investigation is to better inform affective feedback models by providing some measure of confidence that an affective intervention strategy will be beneficial to the student. Therefore, we explored machine learning techniques as an automatic and, perhaps, robust means of classifying candidate feedback strategies as likely to be beneficial or harmful.

To this end, naïve Bayes, decision tree, and support vector machine classification models were induced using the WEKA machine learning toolkit [23]. All models were constructed using a tenfold (within-subjects) cross-validation scheme for producing training and testing datasets, a widely used method for obtaining an acceptable estimate of error [23]. The learned naïve Bayes model performed at 69.5% predictive accuracy, which did not significantly outperform the baseline of 67.8% accuracy. However, both the decision tree (72.9%) and support vector machine (73.11%) models were able to significantly outperform the baseline at $p<0.05$. Linear regression analysis was also performed but did not yield results that outperformed the baseline model.

While these models did offer some improvement over baseline, we predicted that inclusion of the previously learned personality profiles would be able to enhance the predictive power of these models. Therefore, we created a hybrid model, in which a simple naïve Bayes model was created for each reported emotion. These models included only the personality traits that had been previously found to have a significant difference ($p<0.10$) in their prevalence with respect to the populations of students experiencing positive and negative transitions. Naïve Bayes models were specifically chosen for this hybrid as they seemed to be the natural extension from the differentiated probability distributions that make up the personality profiles. They also offer an additional benefit of producing probability distributions for each tested item, which may be used to create a numeric confidence rating to inform future models. These models were again created using ten-fold cross-validation to ensure an appropriate measure of predictive accuracy.

The results of this hybrid model indicated a statistically significant ($p<0.05$) improvement in predictive accuracy over the previously highest performing model, the support vector machine. The hybrid model achieved a predictive accuracy of 75.2%. Interestingly, the predictive accuracies for transitions from some emotional states are significantly higher than others. For instance, the highest predictive accuracy for transitions from the state of *flow* is 84.3% (baseline of 81%). This finding is particularly interesting as the state of flow has been previously identified as a state in which attempting affective intervention is particularly risky [15]. This increase in predictive accuracy for this state may play a role in mitigating the risk of intervention. In contrast, the lowest predictive accuracy (58.8%, baseline of 52%) is in response to students experiencing *frustration.* While such a low predictive accuracy is less than would desired, previous work has suggested that there is little risk in intervening during negative states such as frustration. It is unlikely that the student can experience harmful side-effects from intervention, so in this case we are less concerned about obtaining a good measure of confidence before deciding to pursue an affect intervention strategy.

5.4 Limitations

While the results of this analysis are promising, there are several limitations that must be considered. First, though the affect corpus included over one thousand affect reports from 115 subjects, some affective states are still reported in a very low frequency. In particular, the states of *anger* and *delight* were reported with very low frequencies (fewer than 30 reports each), so it is unclear how appropriate it is to draw conclusions about these states. Additionally, these analyses examined only the interactions between personality characteristics and affective states. It would be particularly interesting to understand how events and progress within the interactive environment also contributed to this complex interaction.

6 Conclusion

The ability to understand and respond to student affective states during learning has been recognized as an important goal for the ITS community. Unfortunately, intervening with student affective states is inherently risky. Therefore, developing affective support models that can consider utility, risk and confidence information is an important step in ensuring beneficial interactions with students. This paper has shown that students' personality characteristics can impact how students respond to attempts to provide affective scaffolding. The personality profiles developed through analysis of an affect corpus were able to enhance the predictive capability of models aimed at determining whether an intervention strategy was likely to have positive outcomes. Additionally, accuracy was especially high in affective states where mitigating risk is of highest importance, suggesting that incorporating these models into future affective feedback paradigms may add significant benefit.

In addition to furthering the development of effective feedback models, the analyses of the affect corpus revealed interesting relationships between certain characteristics and emotional states. For instance, we find that goal orientation traits are more closely tied with emotions associated with learning rather than other emotional states. We additionally find support for the notion that individuals with particular traits have unique "optimal" states that should not be interrupted.

The results of these analyses suggest many interesting directions for future work. For instance, certain emotions, such as *anger,* appeared to have correlations with student characteristics that were inconsistent with other emotional states and seemed to contradict expectations. Further exploration of these anomalies may reveal interesting information regarding the unique characteristics of each of these emotions. Another direction for future work is including event traces for informing models. Detailed information about the student's progress and experience in the environment may help to better inform affective feedback models. Finally, an important next step is incorporating these findings into a comprehensive affect feedback model that is able to better gauge risk, assess confidence and provide feedback in the most appropriate and beneficial manner.

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