Affective Transitions in Narrative-Centered Learning Environments

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Abstract. Affect has been the subject of increasing attention in cognitive accounts of learning. Many intelligent tutoring systems now seek to adapt pedagogy to student affective and motivational processes in an effort to increase the effectiveness of tutorial interaction and improve learning outcomes. To this end, recent work has begun to investigate the emotions experienced during learning in a variety of environments. In this paper we extend this line of research by investigating the affective transitions that occur throughout narrative-centered learning experiences. Further analysis differentiates the likelihood of affective transitions stemming from pedagogical agent empathetic responses to student affect.

1 Introduction

Affect has begun to play an increasingly important role in intelligent tutoring systems. The ITS community has seen the emergence of work on affective student modeling [8], detecting frustration and stress [6, 19, 24], modeling agents' emotional states [1, 15], devising affectively informed models of social interaction [16, 21, 23], detecting student motivation [25], and diagnosing and adapting to student self-efficacy [5]. 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.

Recent work seeking to characterize the affective experience of learners interacting with intelligent learning environments has considered student affective trajectories occurring during learning. D'Mello *et al.* [11] studied the likelihood of affective transitions among six affective states (boredom, flow, confusion, frustration, delight, and surprise) that were found to be relevant to complex learning [9]. In general, learners are likely to persist in the same affective state (e.g., transitioning from a state of boredom to boredom is likely, and in some cases, significantly more likely than transitioning to another affective state). This analysis was conducted in the AutoTutor learning environment [9, 11]. Baker *et al.* were able to replicate many of D'Mello *et al.*'s [11] findings when they calculated the likelihood of affective transitions in the Incredible Machine: Even More Contraptions, a simulation-based learning environment [3]. Baker *et al.* extend their analyses to investigate how usage choices [2] affect emotion transitions. This work found that confused learners are likely to game the system. Further, it was found that students who game the system are unlikely to transition into a confused state [3].

In this paper we investigate the likelihood of affective transitions in a narrative-centered learning environment, CRYSTAL ISLAND. The CRYSTAL ISLAND environment utilizes narrative as a mechanism to contextualize learning, making the experience meaningful. Contextualized learning experiences are known to encourage regulated learning behavior [22] and influence student learning and motivation [18]. Because CRYSTAL ISLAND incorporates an engaging storyline into the learning experience, we supplement the known relevant emotions to learning used by D'Mello *et al.* [11] and Baker *et al.* [3] with affective states that may be relevant to the story (anger, anxiety, boredom, confusion, delight, excitement, fear, flow, frustration, and sadness). We extend our analysis of affective transitions to evaluate the impact of character empathetic responses (parallel vs. reactive empathy) to student affect and the relative impact on transitions.

The paper is organized as follows. Section 2 describes CRYSTAL ISLAND, the narrative-centered learning environment that has been developed in our lab for the domains of microbiology and genetics. Section 3 presents the experimental method utilized for collection of student affective experiences. In Section 4 we report findings on probable transitions in narrative-centered learning and present analyses of the impact of empathy on such transitions. Results are discussed in Section 5. Section 6 notes the limitations of the work, followed by conclusions and future work in Section 7.

2 Crystal Island

The CRYSTAL ISLAND environment is being created for 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, attempting to discover the genetic makeup of the chickens whose eggs are carrying an unidentified infectious disease at the research station. The story opens by introducing the student to the island and the members of the research team for which her father serves as the lead scientist. 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 hypotheses, collecting data, and testing her hypotheses. Throughout the mystery, she can walk around the island and visit various locations. 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 choose which breeds of chickens need to be banned from the island.

The virtual world of CRYSTAL ISLAND, the semi-autonomous characters that inhabit it, and the user interface were implemented with Valve Software's Source™ engine, the 3D game platform for Half-Life 2. The Source engine also provides much of the low-level (reactive) character behavior control. The character behaviors and artifacts in the storyworld are the subject of continued work.

Fig 1. Overview of CRYSTAL ISLAND.

Fig 2. The user, Alex, with Jin, the camp nurse on CRYSTAL ISLAND.

The following scenario illustrates a student's interactive narrative experience in CRYSTAL ISLAND. In the course of having members of her research team become ill, she has learned that an infectious disease is an illness that can be transmitted from one organism to another. As she concludes her introduction to infectious diseases, she learns from the camp nurse that the mystery illness seems to be coming from eggs laid by certain chickens and that the source of the disease must be identified. The student discovers through a series of tests that the bad eggs seem to be coming from chickens with white-feathers. The student then learns that this is a codominant trait and determines that any chicken containing the allele for white-feathers must be banned from the island immediately to halt the spread of the disease. The student reports her findings back to the camp nurse.

3 Methods

3.1 Participants

The subjects of the study consisted of 35 graduate students ranging in age from 21 to 60 (M = 24.4, SD = 6.41) including 9 females and 26 males. Among these students, 60% were Asian (n = 21), approximately 37% were Caucasian (n = 13) and one participant chose not to respond.

3.2 Procedure

Participants entered the experiment room where they completed informed consent documentation. They were randomly assigned to either the control condition or the empathy condition 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 [12], and the goal orientation survey [14].

Upon completing the pre-experiment questionnaires, participants were instructed to review CRYSTAL ISLAND instruction materials. These materials consisted of the backstory and task description, the character overviews, the 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 summarizing the task and 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 35 minutes to solve the mystery. Solving the mystery consisted of completing 15 goals including learning about various diseases, compiling the symptoms of the sickened researchers, testing a variety of possible sources, and reporting the solution (cause and source) back to the camp nurse.

Six CRYSTAL ISLAND characters (Audrey, Elise, Jin, Quentin, Robert, and Teresa), each play distinct roles in the CRYSTAL ISLAND environment. When subjects decided to interact with these particular characters, they were greeted with empathetic reactions to their expressed affective state, which they communicated through self-reports via an in-game dialog. The self-report dialog asked participants to select the affective state that best described their feelings at that time from a set of 10 affective states (anger, anxiety, boredom, confusion, delight, excitement, fear, flow, frustration, and sadness). This set of emotions was comprised of emotions identified with learning [9, 11, 16] together with basic emotions [13] that may play a role in students' experience of the CRYSTAL ISLAND narrative.

Immediately after solving the science mystery of CRYSTAL ISLAND (or after 35 minutes of elapsed interaction time for subjects who had not solved the mystery), subjects completed a post-experiment questionnaire. This researcher-designed questionnaire assessed perceptions of individual CRYSTAL ISLAND characters. The results of this instrument are outside the scope of this discussion.

4 Results

In this section we first present findings regarding common affective transitions observed in CRYSTAL ISLAND. These findings are followed by an analysis comparing and contrasting likely affective transitions stemming from parallel and reactive empathetic reactions by CRYSTAL ISLAND characters.

To compute transition likelihoods we adopt D'Mello *et al.*'s *L* [11], which is based on Cohen's Kappa [7], and has been used by Baker *et al.* for affective transition analysis in their simulation learning environment [3]. *L* computes the probability that a transition between two affective states (CURRENT → NEXT) will occur, where CURRENT refers to a reported emotion at time *t*, while NEXT refers to the next reported emotion at time *t*+1. D'Mello *et al.*'s *L* accounts for the base frequency of the NEXT affective state in assessing the likelihood of a particular transition. Formally,

$$\boldsymbol{L}\,(\text{Current} \rightarrow \text{Next}) = \frac{P(\text{ Next} \mid \text{Current }) - P(\text{ Next })}{1 - P(\text{ Next })}$$

L's numerator is divided by 1-P(NEXT) to normalize scores between -∞ and 1 [11]. A result of *L* equal to 1 translates to emotion NEXT always following the CURRENT emotion; an *L* value equal to 0 means the likelihood of transitioning to emotion NEXT is equal to chance, i.e., the probability of experiencing NEXT (the base rate) regardless of the CURRENT emotion. An *L* value less than 0 translates to the likelihood of

Table 1. Likelihoods for all transitions CURRENT → NEXT for the affective states: **Fr**ustration, **Fl**ow, **Co**nfusion, **De**light, **Bo**redom, **Anx**iety, **Ex**citement, **Ang**er, **Sa**dness, and **Fe**ar.

	Next									
Current	***Fr***	***Fl***	***Co***	***De***	***Bo***	***Anx***	***Ex***	***Ang***	***Sa***	***Fe***
Fr	0.28	-0.19	0.10	-0.05	-0.07	-0.15	-0.10	-0.02	-0.01	0.09
Fl	-0.04	0.19	0.04	0.02	-0.01	0.03	-0.07	0.01	0.00	0.00
Co	0.04	0.04	0.16	-0.03	0.05	-0.04	0.10	-0.01	-0.01	-0.03
De	0.01	0.10	-0.13	0.21	-0.03	-0.05	-0.33	-0.02	0.00	0.00
Bo	0.13	-0.03	-0.03	-0.08	0.13	-0.04	-0.04	0.00	-0.03	0.04
Anx	-0.08	0.06	0.04	-0.07	-0.01	0.14	-0.19	0.09	0.00	0.00
Ex	-0.05	-0.11	0.06	-0.03	-0.03	0.03	0.24	-0.01	0.01	-0.02
Ang	0.00	-0.07	0.09	-0.39	0.00	0.23	0.01	0.00	0.00	0.00
Sa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fe	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

transitioning to emotion NEXT being less than chance (the probability of experiencing NEXT regardless of the CURRENT emotion).

To characterize affective transitions we first compute L for each transition (CURRENT → NEXT), for each student. We then use mean L values across students to determine the likelihood of transitioning from each emotion CURRENT to each emotion NEXT. The results of ANOVAs determine whether the differences in likelihoods of transitioning to each NEXT emotion are significantly different for particular CURRENT emotions.

4.1 Affective Transitions

Aggregating self-reported affective states across the 35 participants we find flow to be the most frequently reported state (42%), followed by excitement (14%), confusion (13%), delight (11%), anxiety (8%), frustration (6%), boredom (3%), sadness (2%), anger (1%), and fear (1%).

ANOVAs indicated that six affective states had statistically significant differences among the likelihoods of transitions. Affective transitions were statistically significantly different transitioning from frustration ($F(9, 340) = 2.06$, $p = 0.03$), flow ($F(9, 340) = 18.3$, $p < 0.0001$), confusion ($F(9, 340) = 1.79$, $p = 0.06$), delight ($F(9, 340) = 5.22$, $p < 0.0001$), anxiety ($F(9, 340) = 2.98$, $p = 0.002$), and excitement ($F(9, 340) = 2.62$, $p = 0.006$).

Frustrated learners are most likely to remain frustrated (Mean $L = .28$) followed by transitions to confusion (.10) and fear (.09). The remaining transitions were below chance levels (i.e., flow (-.19, $t(34) = -4.24$, $p < 0.0001$) and excitement (-.10)).

Learners in the state of flow were most likely to remain in flow (.19) followed by confusion (.04, $t(34) = -3.09$, $p = 0.003$), anxiety (.03), and delight (.02). Both frustration (-.04, $t(34) = -7.91$, $p < 0.0001$) and excitement (-.07) were below chance levels. The remaining transitions did not occur or occurred at chance levels.

Confused students were likely to remain in a confused state (.16) followed by excitement (.10), boredom (.05), frustration (.04), and flow (.04). The likelihood of these and all remaining conditions are summarized in Table 1.

4.2 Affective Transitions by Empathy

Empathy is the expression of emotion based on another's situation and not merely one's own [12]. Its expression can demonstrate that the target's (the recipient of empathetic expression) feelings are understood or shared. In the case of *parallel empathy*, an individual exhibits an emotion similar to that of the target [12]. This is typically based on an understanding of the target's situation and shows the empathizer's ability to identify with the target. *Reactive empathy*, in contrast, focuses on the target's affective state, in addition to her situation [12]. Reactive empathizers will display emotions that are different from the target's, often in order to alter or enhance the target's own affective state. This type of empathy is focused on the target whereas parallel empathy is more self-oriented. As such, reactive empathy can be viewed as a higher level of empathetic behavior.

Recent research with the characters of CRYSTAL ISLAND has investigated the merit of providing characters with empathetic capabilities to effectively respond to unfolding student experiences [20]. In CRYSTAL ISLAND, empathetic responses are short, text-based responses consisting of 1 to 2 sentences. Parallel responses consist of the character expressing the same emotion as the user through text responses. On the other hand, reactive responses demonstrate advanced cognitive processing on the character's part by providing responses designed to be more motivating and thus revealing the character's desire for the user to be in a positive emotional state. The results below investigate the likelihood of affective transitions based on empathetic expressions by CRYSTAL ISLAND characters in response to student CURRENT emotions. The findings suggest that in certain situations, parallel and reactive empathy have significant differences in the affective transitions (NEXT emotion) that are likely to occur.

While the relatively low frequencies of some transitions prevent many of the visible differences from being statistically significant, interesting patterns do emerge. Figures 3 and 4 present the transitions from the state of flow and frustration by empathetic reaction type (parallel or reactive). Analyzing the transitions from the state of flow we find that parallel empathy (.11) is somewhat significantly more likely to support students' remaining in the state of flow than reactive empathy (-.05), $t(12) = -2.08$, $p = 0.06$. Similarly, we find that the likelihood of transitioning to frustration from a frustrated state is significantly more likely when characters empathetic reactions are parallel in nature (.57) than reactive (-.13), $t(12) = -2.09$, $p = 0.059$. Other patterns with visible differences emerging from this analysis of affective transitions are summarized in Table 2. Although the transition frequencies were not sufficiently high for the differences to be statistically significant, they merit discussion.

Table 2. Interesting likelihood for transitions differences by empathetic response type (parallel or reactive).

CURRENT	***Transition State (NEXT)***	***Parallel Empathy Likelihood***	***Reactive Empathy Likelihood***
Boredom	Boredom	.35	-.04
	Confusion	0	-.41
	Flow	-.13	.32
	Frustration	-.08	.26
Anxiety	Anxiety	.33	.05
	Frustration	-.20	.17
Frustration	Frustration	.57	-.13
	Flow	.10	-.25
	Confusion	-.17	.15
Flow	Flow	.11	-.05
	Confusion	.04	.08
Delight	Delight	.21	.21
	Flow	.07	.17

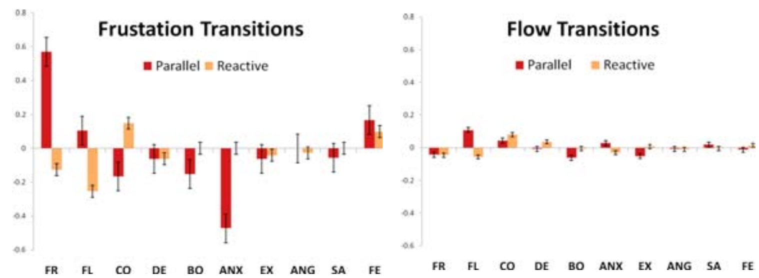

Fig. 3. Transitions from frustration and flow to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **AN**xiety, **EX**citement, **AN**ger, **SA**dness, and **FE**ar.

5 Discussion

The analysis of affective state transitions in CRYSTAL ISLAND replicate findings by D'Mello *et al.* [11] and Baker *et al.* [3]. For instance, the state of flow dominated self-reported affect. The dominance of the flow state has been reported in a number of affective studies with intelligent learning environments [3, 9, 11]. Frustration and boredom were reported notably less frequently than in D'Mello *et al.*'s study and was comparably reported to frequencies found in Baker *et al.* Perhaps surprisingly, emotions found to be relevant to learning (boredom, confusion, delight, flow, and frustration) were more prevalent than the narrative affective states (anger, excitement, fear, and sadness) hypothesized to be relevant affective outcomes to experiencing the CRYSTAL ISLAND story.

Among the most likely transitions were transitions where NEXT = CURRENT. This was true for the affective states frustration, flow, confusion, delight, boredom, anxiety, excitement, and anger. This result also replicates the findings of [11] and [3]. D'Mello termed these cycles *vicious cycles* for negative affective states (similar to Burleson's notion of "state of stuck" [6]) and *virtuous cycles* when students are likely to stay in positive states (i.e., flow).

When we consider affective transitions where NEXT occurs at time *t+1* after an empathetic response from a CRYSTAL ISLAND character, we notice differences in the likely affective outcomes. For instance, if a student is in a frustrated state, parallel empathy is likely to elicit a transition in which the student stays frustrated. In contrast, reactive empathy is less likely than chance to prompt the same vicious cycle. Instead reactive empathy tends to promote transitions to a confused state, which is known to have better correlations with learning [9].

When we consider likely transitions from the state of flow, we find that parallel empathy is likely to encourage students to enter a virtuous cycle and remain in the state of flow. Reactive empathy is less likely than chance to produce the flow state and is likely to promote an affective state transition to confusion. Since a flow state is an optimal state of experience [10], we can understand why reactive empathy cannot motivate students to enter a more engaged state.

Analyzing transition patterns from the state of boredom, we find parallel empathy is likely to encourage a vicious cycle while reactive empathy is less likely than chance to produce the same cycle. Instead, reactive empathy is most likely to transition to flow, with frustration slightly less likely than flow. In the future, when we can accurately predict when reactive empathy is likely to encourage flow as opposed to when it is likely to promote frustration, this diagnostic information can inform pedagogical agents' empathetic responses to alleviate student boredom and promote a state of flow.

6 Limitations

The results of this study are affected by the virtual characters that interacted empathetically with participants. It is possible that the gender, narrative role, and pedagogical role of the characters may affect the likelihood of transitions in addition to the type of empathy. Another shortcoming is that affective states were solely collected from student self-reports. In contrast, both D'Mello et al [11] and Baker *et al.* [3] used judged reports of affect in their transition analysis. In the study reported here, video recordings of participants' faces were collected during their interactions with the learning environment to permit future work to consider judged reports of affect with this dataset. Finally, to determine how broadly the results hold, the transitions that were found to be likely with this subject population need to be validated with other populations, such as the intended population of middle school student users.

7 Conclusion

Given the central of role of affect and motivation in cognitive processes, it is becoming increasingly more important for intelligent tutoring systems to consider the affective experiences of students. This study replicates the findings of studies conducted with AutoTutor [11] and The Incredible Machine simulation-based learning environment [3], including a demonstration of the prominence of the state of flow during learning. By extending our analysis to consider how affective transitions differ given empathetic character responses, the findings can inform the design of heuristics for pedagogical agents to determine when the use of empathy is likely to have desired outcomes and what type of empathy (parallel or reactive) would be best utilized. Such analysis can also inform the utility induced models of empathy [20].

The results suggest two directions for future work. First, they call for investigation of what type of feedback pedagogical agents should consider when empathy does not promote desirable affective states for learning. For instance, reactive empathy was likely to encourage transitions to either flow or frustration. In instances where empathy promoted frustration we should determine why empathy does not work and what type of system response would be more appropriate. Second, analysis of individual differences is necessary to determine the affective transitions common across a variety of demographics such as gender, but also across learning attributes such as efficacy, goal orientation, interest, and abilities to self-regulate both learning and affect.

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