McQuiggan, S. W., Robison. J. L., & Lester, J. C. (2010). Affective Transitions in Narrative-Centered Learning Environments. *Educational Technology & Society*, *13* (1), 40–53.

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.

Keywords

Affective transitions, Narrative-centered learning environments, Empathetic pedagogical agents

Introduction

Affect has begun to play an increasingly important role in intelligent tutoring systems (ITS). The ITS community has seen the emergence of work on affective student modeling (Conati & Mclaren, 2005), detecting frustration and stress (Burleson, 2006; McQuiggan, Lee, & Lester, 2007; Prendinger & Ishizuka, 2005), modeling student uncertainty (Forbes-Riley & Litman, 2007), modeling agents' emotional states (André & Mueller, 2003; Gratch & Marsella, 2004; Lester, Towns, & FitzGerald, 1999), devising affectively informed models of social interaction (Johnson & Rizzo, 2004; Paiva et al., 2005; Porayska-Pomsta & Pain, 2004; Wang et al., 2008), detecting student motivation (de Vicente & Pain, 2002), and diagnosing and adapting to student self-efficacy (Beal & Lee, 2005; McQuiggan, Mott, & Lester, 2008). 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, Taylor, & Graesser (2007) 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 (Craig, Graesser, Sullins, & Gholson, 2004). 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 (Craig et al., 2004; D'Mello et al., 2007). Baker, Corbett, Koedinger, & Wagner (2004) were able to replicate many of D'Mello et al.'s (2007) findings when they calculated the likelihood of affective transitions in the Incredible Machine: Even More Contraptions, a simulation-based learning environment (2007). Baker et al. (2004) extend their analyses to investigate how usage choices 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 (Baker, Rodrigo, & Xolocotzin, 2007).

In this article we investigate the likelihood of affective transitions in a narrative-centered learning environment, CRYSTAL ISLAND. The CRYSTAL ISLAND environment uses narrative as a mechanism to contextualize learning, making the experience meaningful. Contextualized learning experiences are known to encourage regulated learning behavior (Perry, 1998) and influence student learning and motivation (Linnenbrink & Pintrich, 2001). 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. (2007) and Baker et al. (2007) 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. We further extend our analysis to investigate whether

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additional factors may affect the frequency of transitions between affective states, turning our attention to characteristics of the students. We have chosen four characteristics to examine based on their potential influence on learning and reaction to the learning environment: gender, personality, goal orientation, and presence.

The article is organized as follows. First we describe CRYSTAL ISLAND, the narrative-centered learning environment that has been developed in our lab for the domains of microbiology and genetics. Next, we present the experimental method utilized to study student affective experiences. We then report findings on probable transitions in narrative-centered learning and present analyses of the impact of empathy on such transitions. We discuss results and note limitations, then provide conclusions and an indication of future work.

CRYSTAL ISLAND

The CRYSTAL ISLAND environment (Figure 1 and Figure 2) 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, who attempts to discover the genetic makeup of the chickens at the research station whose eggs carry an unidentified infectious disease. The story opens by introducing the student to the island and the members of the research team for which the student's father serves as the lead scientist. As members of the research team fall ill, it is the student's 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 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.

Figure 1. Overview of CRYSTAL ISLAND

Figure 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 learns 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 co-dominant 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.

Method

After describing the participants, we introduce the experimental design. We then present the results and discuss the affective transitions observed in narrative-centered learning experiences.

Participants

The subjects of the study were 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) and approximately 37% were Caucasian (n = 13). One participant chose not to respond.

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 (Davis, 1994), the goal orientation survey (Elliot & McGregor, 2001), and the personality questionnaire (McCrae & Costa, 2003).

Upon completing the pre-experiment questionnaires, participants were instructed to review CRYSTAL ISLAND instruction materials. These materials consisted of the backstory and task description, character overviews, a map of the island, a control sheet, and a 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 (Craig et al., 2004; D'Mello et al., 2007; Kort et al., 2001), together with basic emotions (Ekman & Friesen, 1978) 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. Additionally, participants' presence experience was captured with the presence questionnaire (PQ), which was developed and validated by Witmer and Singer (1998). The PQ contains several subscales, including involvement/control, naturalism of experience, and quality of the interface scales. The PQ accounts for four categories of contributing factors of presence: control, sensory, distraction, and realism.

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* (2007), which is based on Cohen's Kappa (1960), and has been used by Baker et al. for affective transition analysis in their simulation learning environment (2007). *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 (2007). Formally,

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

Table 1. Likelihoods for all transitions *Current* → *Next* for the affective states:
Frustration, **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

L's numerator is divided by $1-P(Next)$ to normalize scores between $-\infty$ and 1 (2007). 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, that is, the probability of experiencing *Next* (the base rate) regardless of the *Current* emotion. An *L* value less than 0 translates to the likelihood of 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.

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 ($F(9, 340) = 2.06$, $p = .03$), flow ($F(9, 340) = 18.3$, $p < .0001$), confusion ($F(9, 340) = 1.79$, $p = .06$), delight ($F(9, 340) = 5.22$, $p < .0001$), anxiety ($F(9, 340) = 2.98$, $p = .002$), and excitement ($F(9, 340) = 2.62$, $p = .006$).

Notably, frustrated learners are most likely to remain frustrated (Mean $L = .28$) followed by transitions to confusion (0.10) and fear (0.09). The remaining transitions were below chance levels (i.e., flow (−0.19, $t(34) = -4.24$, $p < .0001$) and excitement (−0.10)).

Table 2. Interesting likelihood for transition 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

Learners in the state of flow were most likely to remain in flow (0.19) followed by confusion (.04, $t(34) = -3.09$, $p = .003$), anxiety (0.03), and delight (0.02). Both frustration (−0.04, $t(34) = -7.91$, $p < .0001$), and excitement (−0.07) 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 (0.16) followed by excitement (0.10), boredom (0.05), frustration (0.04), and flow (0.04). The likelihood of these and all remaining conditions is summarized in Table 1.

Affective transitions by empathy

Empathy is the expression of emotion based on another's situation and not merely one's own (Davis, 1994). Its expression can demonstrate that the feelings of the target (the recipient of empathetic expression) are understood or shared. In the case of parallel empathy, an individual exhibits an emotion similar to that of the target (Davis, 1994). 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 (Davis, 1994). 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 (McQuiggan, Robison, Phillips, & Lester, 2008; McQuiggan, Rowe, & Lester, 2008). In CRYSTAL ISLAND, empathetic responses are short, text-based responses consisting of one or two 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, 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* emotions) 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. Figure 3 and Figure 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 (0.11) is somewhat significantly more likely to support students' remaining in the state of flow than reactive empathy (−.05), $t(12) = -2.08$, $p = .06$. Similarly, we find that the likelihood of transitioning to frustration from a frustrated state is significantly greater when characters' empathetic reactions are more parallel in nature (0.57) than reactive (−0.13), $t(12) = -2.09$, $p = .059$. 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.

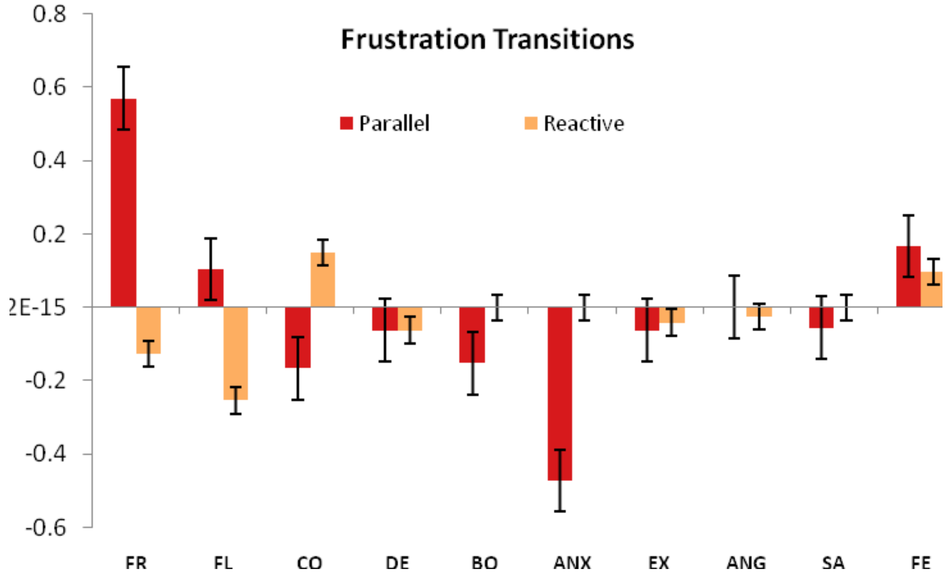

Figure 3. Transitions from frustration to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar

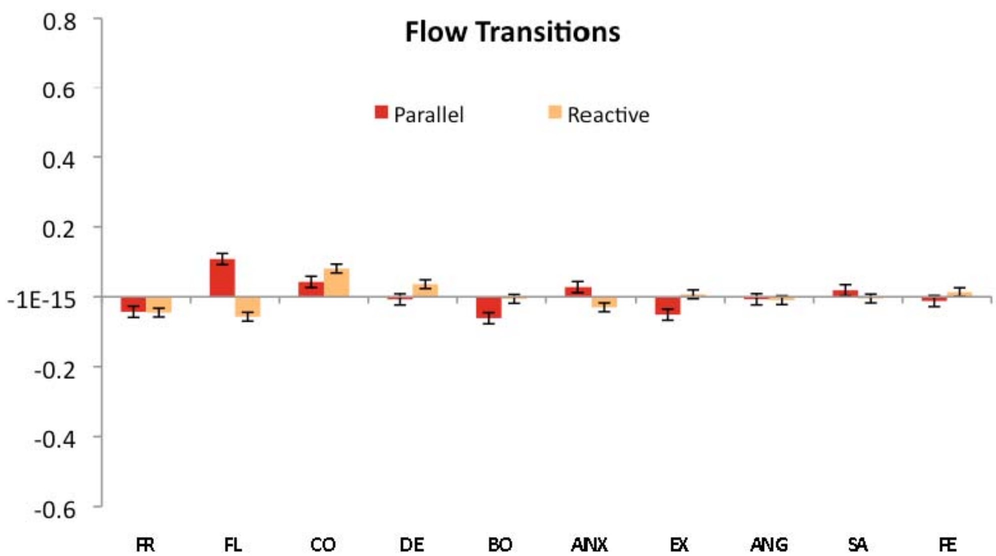

Figure 4. Transitions from flow to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar

Student characteristics results

In this section we analyze the individual differences with which affective states are reported. This examination includes demographics, personality, goal orientation, and presence. These findings are followed by a summary of individual differences in affective transitions.

Gender refers to an individual's identification as male or female. Interestingly, significant differences have been found in how male and female students approach learning tasks. For example, women are more likely than men to perceive intelligence as an immutable entity that cannot be improved with increased focus on learning tasks (Lips, 2007). This belief may mean that women are more likely to experience negative emotions such as frustration and confusion, and also experience vicious cycles (D'Mello et al., 2007). In this case, intervention would be necessary to break students of this cycle and encourage a more dynamic approach to learning.

Personality is an individual's disposition over a long duration of time, distinguishing itself from emotions or moods that are more limited in their duration (Rusting, 1998). Using the Big 5 Personality Questionnaire (McCrae & Costa, 2003), personality is divided into five main categories: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Of particular interest among these are openness, conscientiousness, and neuroticism, as these characteristics are likely to affect emotion and learning. Additionally, since information on affective states was obtained through self-report, we expect to find that 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 (Elliot & McGregor, 2001). A performance approach would result in a student's wishing to prove his or her competence and achieve better results than other students. Students with a mastery approach, however, view learning as an attempt to gain a skill, regardless of how their ability compares to others. In addition, 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 students.

Presence relates to the level of student involvement within the system (Witmer & Singer, 1998). Students who experience high levels of presence will be very engaged with the activity, focusing solely on the task while neglecting their external environment. We expect that these students will experience more salient affective states and have more intense reactions to events within the system. Additionally, significant differences in transitions between students who are and are not present may be able to serve as an indicator of presence.

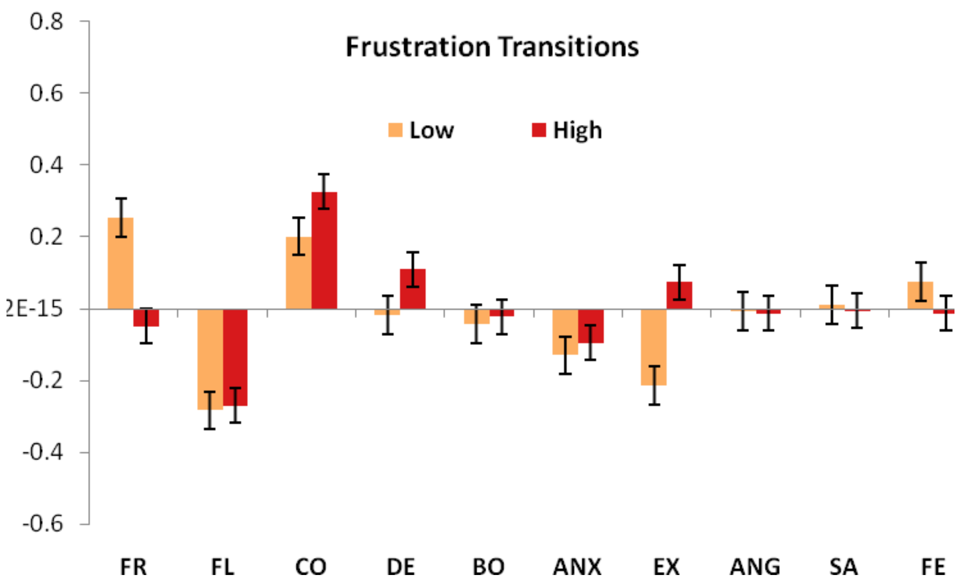

Figure 5. Transitions from frustration to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar by level of agreeableness

There were significant differences in the frequencies with which male and female participants reported emotions of boredom. Females (n = 9) did not report feeling bored while the males did, leading to a marginally significant difference, $t(34) = 1.87$, $p = .07$. There were no other significant differences across gender. Student personalities also affected the frequency with which certain affective states were reported, namely, anger, boredom, confusion, delight, and flow. There was a significant difference in the frequency of reported states of flow along the extraversion dimension. Students who were more extraverted reported affective states of flow less frequently than less extraverted students, $t(34) = 2.14$, $p = .04$. Also along the extraversion dimension were differences in the frequencies of delight and anger. Marginally significant was the frequency of which the more extraverted students reported delight than did the less extraverted students, $t(34) = 1.82$, $p = .07$. The more extraverted students reported delight approximately five times per interaction compared to just two times for the less extraverted students. Anger was reported more frequently by the more extraverted students than by the less extraverted students, $t(34) = 2.77$, $p = .009$.

There were significant differences across the personality dimensions of agreeableness (Figure 5 and Figure 6), conscientiousness, and neuroticism in reports of confusion. The less agreeable students reported confusion more frequently ($M = 6.06$, $SD = 1.5$) than the more agreeable students ($M = 2.36$, $SD = 1.4$), $t(34) = 1.77$, $p = .08$. Similarly, the less conscientious students reported confusion more frequently ($M = 6.0$, $SD = 1.43$) than the more conscientious students ($M = 2.0$, $SD = 1.47$), $t(34) = 1.94$, $p = .06$. Students with greater emotional stability (neuroticism dimension) reported confusion more frequently ($M = 7.93$, $SD = 1.48$) than the less emotionally stable students ($M = 1.47$, $SD = 1.2$), $t(34) = 3.37$, $p = .001$. The final significant difference in emotion frequencies along personality dimensions is reports of boredom across student agreeableness. The more agreeable students reported being bored less frequently ($M = 0.1$ $SD = 0.4$) than the less agreeable students ($M = 2.2$ $SD = 0.44$), $t(34) = 3.45$, $p = .001$.

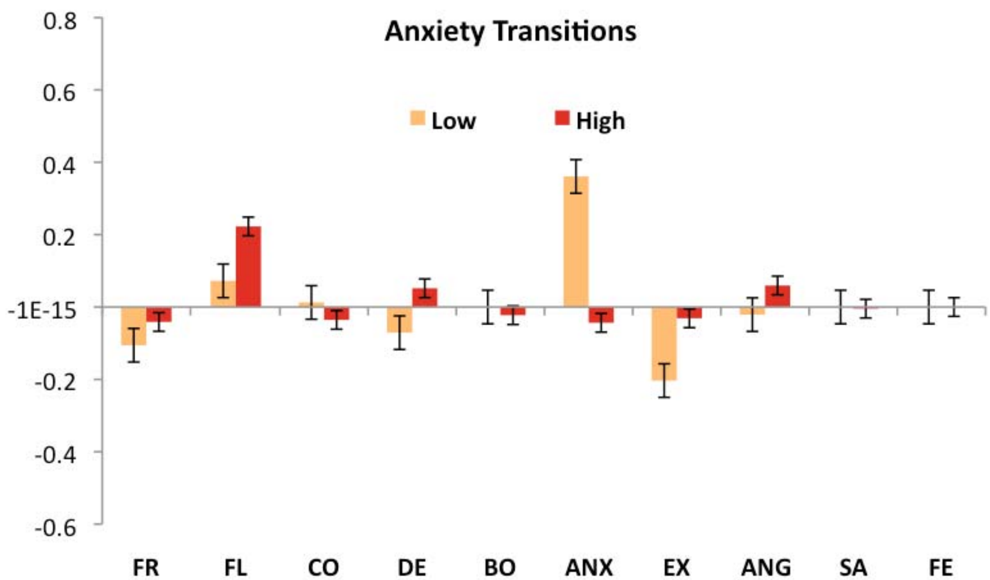

Figure 6. Transitions from anxiety to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar by level of agreeableness

Student goal orientation (Figure 7 and Figure 8) also affected the frequency of which students reported anger, anxiety, and flow. Anger was reported more frequently by students scoring higher on the performance approach subscale than students scoring below the performance approach population mean, $t(34) = 2.28$, $p = .03$. Marginally significant was the increased frequency with which students who were dominantly performance oriented reported feeling anxious ($M = 3.62$, $SD = 0.89$) than students who were dominantly mastery oriented ($M = 1.2$, $SD = 1.1$), $t(34) = 1.71$, $p = .09$. Also significant was the frequency with which students scoring high on the performance avoidance subscale reported feeling anxious ($M = 4.05$, $SD = 0.87$) compared to students scoring below the performance avoidance population mean ($M = 0.8$, $SD = 1.01$), $t(34) = 2.43$, $p = .02$. Flow was more frequently reported by students who were dominantly mastery oriented ($M = 18.2$, $SD = 2.8$) than students who were dominantly performance oriented ($M = 10.04$, $SD = 2.2$), $t(34) = 2.25$, $p = .03$. The frequency of flow reports was impacted by students' performance orientations. Students scoring lower on the performance avoidance subscale reported more feelings of flow than students scoring above the performance avoidance population mean, $t(34) = 2.13$, $p = .04$. Comparatively, students scoring lower on the performance approach subscale reported more feelings of flow than students scoring above the population mean for performance approach, $t(34) = 1.87$, $p = .07$.

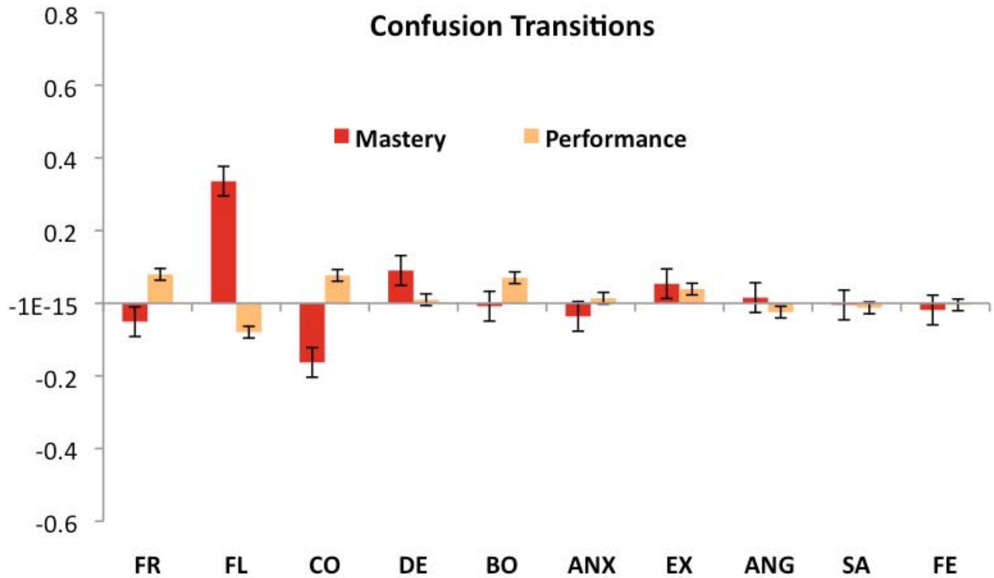

Figure 7. Transitions from confusion to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar by dominant goal orientation

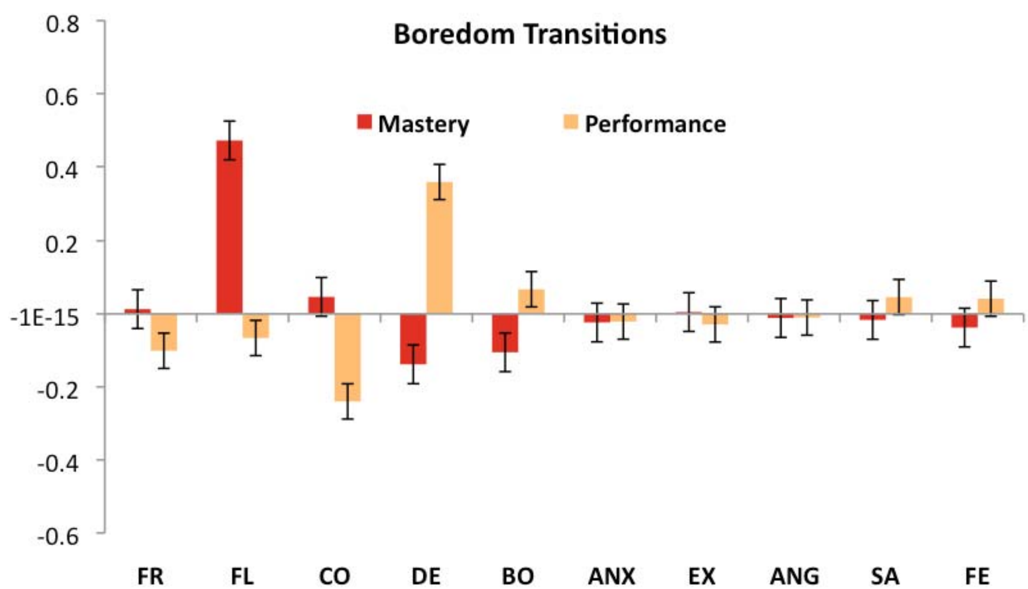

Figure 8. Transitions from boredom to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar by dominant goal orientation

Lastly, there were differences in the frequency of reports of frustration and anxiety across students' reported sense of presence (Figure 9 and Figure 10). Students scoring below the population mean of the presence questionnaire reported frustration with greater frequency than students reporting a greater sense of presence with marginal significance, $t(34) = 1.70$, $p = .09$. Anxiety was reported more frequently by students scoring above the population mean on the presence questionnaire than by students reporting lower levels of presence, $t(34) = 2.23$, $p = .03$.

There were few statistically significant differences in affective transitions across individual differences. This is likely due to a small population size (n = 35) resulting in small split population sizes. However, there are noticeable trends that may be concretely uncovered in a large-scale study. We report on several of these trend findings below.

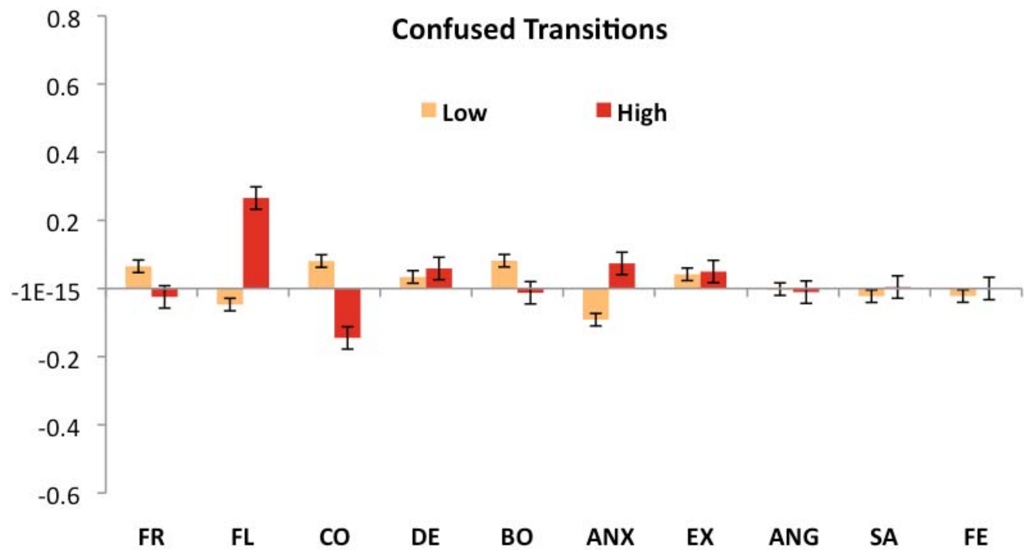

Figure 9. Transitions from confusion to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar by level of reported sense of involvement/control (presence subscale)

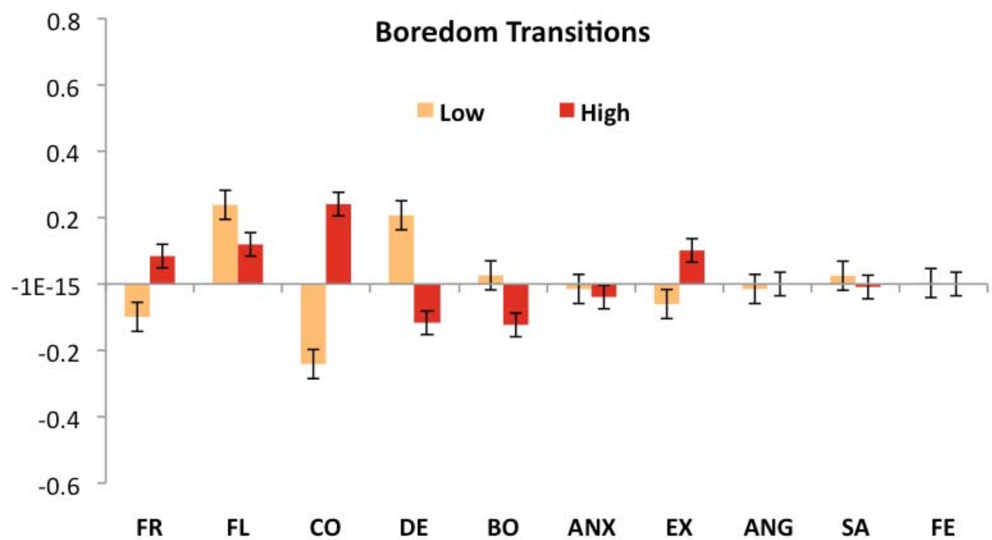

Figure 10. Transitions from confusion and boredom to **FR**ustration, **FL**ow, **CO**nfusion, **DE**light, **BO**redom, **ANX**iety, **EX**citement, **ANG**er, **SA**dness, and **FE**ar by level of reported sense of involvement/control (presence subscale)

For example, there are interesting differences in affective transitions when we consider student dominant-goal orientations. Mastery-oriented students are not likely to stay confused and are most likely to transition to a state of flow, a finding that suggests that mastery-oriented students are engaged or motivated by the cognitive disequilibrium associated with confusion. Being in a confused state is associated with a need to learn, and the CRYSTAL ISLAND environment supports mastery-oriented students' goal of acquiring knowledge. There is a chance that performance-oriented students may stay confused or transition to negative states such as frustration, boredom, or anxiety. Perhaps this is indicative of the fact that CRYSTAL ISLAND is guiding performance-oriented students into situations where they must master content to proceed, thus slowing progress and inadvertently decreasing perceived performance. Also, we notice that bored mastery-oriented students are not likely to remain bored and are more likely to transition to a state of flow or confusion. These emotional states are thought to be preferred for learning (Craig et al., 2004).

Lastly, there are interesting differences in likely transitions when we consider reported student presence as well. The participant population was broken into two groups around the population mean for the involvement/control subscale: *low* and *high*. Here we notice that students reporting high levels of involvement are not likely to stay in a state of confusion and are most likely to transition to a state of flow. On the other hand, students reporting lower levels of involvement in their experience were likely to stay confused or transition to other affective states, such as frustration or boredom. We notice a similar trend in transitions from a state of boredom. Students reporting high levels of involvement are not likely to stay bored and are more likely to become confused, excited, or enter a flow state. Students reporting lower levels of involvement are somewhat likely to stay bored, but are surprisingly more likely to transition to flow or delight. However, the occurrences of the vicious boredom cycles may in part be the cause for lower levels of reported involvement and control due to student disengagement.

Discussion

The analysis of affective state transitions in CRYSTAL ISLAND replicate findings by D'Mello et al. (2007) and Baker et al. (2007). 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 (Baker et al., 2007; Craig et al., 2004; D'Mello et al., 2007). Frustration and boredom were reported notably less frequently than in D'Mello et al.'s study (2007) and was comparably reported to frequencies found in Baker et al. (2007). 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 of frustration, flow, confusion, delight, boredom, anxiety, excitement, and anger. This result also replicates the findings of D'Mello et al. (2007) and Baker et al. (2007). D'Mello termed these cycles vicious cycles for negative affective states (similar to Burleson's notion of "state of stuck" [2006]) and virtuous cycles when students are likely to stay in positive states (i.e., flow) (2007).

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 (Craig et al., 2004).

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 (Csikszentmihalyi, 1990), it seems reasonable that reactive empathy cannot motivate students to enter a more engaged state.

Analyzing transition patterns from the state of boredom, we find that parallel empathy is likely to encourage a vicious cycle, whereas 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.

Among the differences between personality traits, those relating to extroversion and conscientiousness are perhaps the most interesting. Highly extroverted individuals were more likely to report narrative-based emotions such as anger and delight and less likely to focus on learning or flow. Perhaps these individuals were more focused on the narrative aspects of the environment, such as interacting with characters, and consequently their attention was drawn away from learning tasks. Additionally, individuals who reported high levels of conscientiousness were less likely to report experiencing confusion. Generally, conscientious individuals are more likely to regulate their own behavior and perhaps this led them to focus on finding solutions to resolve their confusion. This notion was also supported by the increased likelihood of conscientious individuals to transition into flow and the very low likelihood that they remained confused.

Overall, the trend among affective frequencies shows that increased levels of performance orientation leads to reduced levels of flow and increased levels of anxiety. This is true when examining students' dominant orientation as well as their avoidance and approach subscales. This correlates well with understanding the approaches used by these two categories. Individuals who are mastery oriented are focused strongly on learning and may therefore be more likely to immerse themselves in learning-oriented activities in the environment. Similarly, as suggested by the rates of affective transitions, they may return more quickly to flow after experiences of other affective states. Conversely, performance-dominant students are focused on their measures of success. The higher level of anxiety reported by these students may be a direct result of concerns of performance. Because there is no objective measure of performance in the CRYSTAL ISLAND environment, performance-dominant students may become nervous over supposed comparison to others and opinions of the researcher present.

Interestingly, differences were found based on individual reports of presence. Students who reported higher levels of presence were more likely to have been anxious and less likely to have experienced frustration. Perhaps students who became frustrated disengaged themselves from the environment, resulting in lower levels of presence. Also, students who were highly engaged may have felt more salient responses to the narrative aspects of the environment. They may have become more concerned over the wellbeing of the characters and anxious over the outcome of the events. These differences are especially significant as they suggest that anxiety might be used to indicate measures of presence. Similarly, it appears that given an objective of maintaining presence, it would be highly important to avoid frustrating users.

Limitations

It seems likely that the results of this study are influenced 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 limitation is that affective states were solely collected from student self-reports. In contrast, both D'Mello et al. (2007) and Baker et al. (2007) used judged reports of affect in their transition analysis. In the study reported here, participants' faces were videotaped during interactions with the learning environment to permit future work that considers 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.

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. The study reported here replicates the findings of studies conducted with AutoTutor (D'Mello et al., 2007) and The Incredible Machine simulation-based learning environment (Baker et al., 2007), 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 (McQuiggan, Robison, et al., 2008).

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.

Acknowledgments

The authors wish to thank the members of IntelliMedia Center for Intelligent Systems, Omer Sturlovich, and Pavel Turzo for use of their 3D model libraries, and Valve Software for access to the Source engine and SDK. This research was supported by the National Science Foundation under Grants REC-0632450, IIS-0757535, DRL-0822200, IIS-0812291, and CNS-0540523. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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