

Differential Affective Experiences in Narrative-Centered Learning Environments

Jennifer L. Robison, Scott W. McQuiggan, and James C. Lester

Department of Computer Science, North Carolina State University, Raleigh NC 27695
{jlrobiso, swmcquig, lester}@ncsu.edu

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 variances in transitions based upon individual characteristics. The findings reveal how affective trajectories vary among students and how these characteristics impact learning.

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 [7], detecting frustration and stress [5, 19, 22], modeling agents' emotional states [1, 14], devising affectively informed models of social interaction [15, 21], and detecting student motivation [11]. 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, 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. [9] 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 [8]. 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 [8, 9]. Baker et al. [3] were able to replicate many of D'Mello et al.'s [9] 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, they found that students who game the system are unlikely to transition into a confused state [3].

Previously, we have examined the likelihood of affective transitions in the narrative-centered learning environment, CRYSTAL ISLAND [20]. The results of this work show that the occurrence of affective states did not vary significantly from non-narrative-based

learning environments. Similarly, we found that students were most likely to stay in their current affective state, rather than transitioning to another state. Additionally, we examined how empathetic intervention affected the frequency of transitions between states. The results of this study showed that different types of empathetic responses resulted in increased or decreased likelihood of some transitions. For example, frustrated students were very likely to remain frustrated if presented with a character who mimicked their emotions (parallel empathy) but were unlikely to stay in that state if the character encouraged more positive thinking (reactive empathy). Given these results, we now investigate whether additional factors may affect the frequency of transitions between affective states. Here, we turn 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.

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 to perceive intelligence as an immutable entity which cannot be improved with increased focus on learning tasks [17]. This belief may mean that women are more likely to experience negative emotions such as frustration and confusion, and also experience vicious cycles [9]. 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 which are more limited in their duration [23]. Using the Big 5 Personality Questionnaire [18], 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 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 [13]. A performance approach would result in a student wishing to prove their competence and achieve better results than other students. A student with a mastery approach, however, views learning as an attempt to gain a skill, regardless of how their ability compares to others. In addition to these categories, students may have avoidance strategies in relation to their goals. For example, a student 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's involvement within the system [24]. 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.

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, who is 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.

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.

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 immediately to halt the spread of the disease. The student reports her findings back to the camp nurse.

3 Methods

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.

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 [10], the goal orientation survey [13], and the personality questionnaire [18].

Participants were then 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.

When subjects decided to interact with characters, they were greeted and asked to self-report affect 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 [8, 9, 16] together with basic emotions [12] 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 [24]. 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.

4 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. To compute transition likelihoods we adopt D'Mello et al.'s L [9], which is based on Cohen's Kappa [6], and has been used by Baker et al. for affective transition analysis in their simulation learning environment [3] and to analysis how transitions differ across empathetic interventions [20]. L computes the probability that a transition between two affective states (CURRENT $\rightarrow$ 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. For details on affective transitions see [3, 9, 20].

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%). Next, we examine these frequencies for individual differences across gender, personality, goal-orientation, and reported levels of presence.

There were significant differences in the frequencies with which males and females 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 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 extroverted reported affective states of flow less frequently than less extroverted 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 more extroverted students reported

delight than less extraverted students, $t(34) = 1.82, p = .07$. The more extraverted students reported delight almost 5 times per interaction compared to just 2 times for the less extraverted students. Anger was reported more frequently by more extraverted students than less extraverted students, $t(34) = 2.77, p = .009$.

There were significant differences across the personality dimensions of Agreeableness, Conscientiousness, and Neuroticism in reports of confusion. Less agreeable students reported confusion more frequently ($M = 6.06, SD = 1.5$) than more agreeable students ($M = 2.36, SD = 1.4$), $t(34) = 1.77, p = .08$. Similarly, less conscientious students reported confusion more frequently ($M = 6.0, SD = 1.43$) than 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 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. More agreeable students reported being bored less frequently ($M = 0.1, SD = 0.4$) than less agreeable students ($M = 2.2, SD = 0.44$), $t(34) = 3.45, p = .001$.

Student goal orientation 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 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 ($M = 4.05, SD = 0.87$) than 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, $t(34) = 1.87, p = .07$.

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

ANOVAs indicated that six affective states had statistically significant differences among the likelihoods of transitions. Affective transitions were 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 ($F(9, 340) = 2.62, p = 0.006$). These results are detailed in [20].

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.

For instance, 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 [8].

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.

5 Discussion

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. Conscientious individuals are more likely to regulate their own behavior and perhaps this leads them to focus on finding solutions to resolve their confusion. This notion is also supported by the increased likelihood of conscientious individuals to transition into flow and the very low likelihood that they will remain 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 student's dominant orientation as well as their avoidance and approach subscales. This correlates well with understanding of 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 among individual reports of presence. Students reporting higher levels of presence were more likely to be 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 it suggests 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.

6 Conclusion

Given the central role of affect and motivation in cognitive processes, it is becoming increasingly important for intelligent tutoring systems to consider the affective experiences of students. This study replicates the findings of studies conducted with AutoTutor [9] 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 analyses to consider the individual differences of affective experiences and analyze the frequency of affect, we can better inform the design of heuristics for pedagogical agents to determine the implications of student differences.

The results suggest two directions for future work. First, they call for investigation of what type of feedback pedagogical agents should consider when undesirable affective transitions are likely to occur or when students are in vicious cycles. Second, an extensive 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, 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 Grant REC-0632450 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.

References

1. André, E., and Mueller, M. (2003) Learning affective behavior. In *Proceedings of the 10th Intl. Conf. on Human-Computer Interaction*. Lawrence Erlbaum, Mahwah, NJ, 512-516.
2. Baker, R., Corbett, A., Koedinger, K., and Wagner, A. Off-Task Behavior in the Cognitive Tutor Classroom: When Students “Game the System”. *Proceedings of ACM SIGCHI Conference on Human Factors in Computing Systems*, 2004, 383-390.
3. Baker, R., Rodrigo, M., and Xolocotzin, U. The dynamics of affective transitions in simulation problem-solving environments, *Proceedings the 2nd International Conference on Affective Computing and Intelligent Interactions*, Lisbon, Portugal, 2007, 666-677.
4. Baylor, A. and Kim, Y. Pedagogical agent design: The impact of agent realism, gender, ethnicity, and instructional role. In *Proceedings of the 7th International Conference on Intelligent Tutoring Systems*, Springer-Verlag, New York, NY, 2004, 592-403.
5. Burleson, W. Affective learning companions: Strategies for empathetic agents with real-time multimodal affective sensing to foster meta-cognitive and meta-affective approaches to learning, motivation, and perseverance. *PhD thesis*, Massachusetts Institute of Technology, 2006.
6. Cohen, J. A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, 20 (1960), 37-46.
7. Conati, C., and McLaren, H. Data-driven refinement of a probabilistic model of user affect. In *Proceedings of the 10th Intl. Conf. on User Modeling*. Springer-Verlag, New York, NY, 2005, 40-49.
8. Craig, S.D., Graesser, A.C., Sullins, J., Gholson, B. Affect and learning: an exploratory look into the role of affect in learning with AutoTutor. *Journal of Educational Media*, 29(3), 241-250, 2004.
9. D’Mello, S., Taylor, R.S., Graesser, A. Monitoring Affective Trajectories during Complex Learning. *Proceedings of the 29th Annual Meeting of the Cognitive Science Society*, Austin, TX, 2007, 203-208.
10. Davis, M. *Empathy: A Social Psychological Approach*. Brown & Benchmark Publishers, Madison, WI, 1994.
11. de Vicente, A., and Pain, H. Informing the detection of the students’ motivational state: an empirical study. In *Proceedings of the 6th International Conference on Intelligent Tutoring Systems*. Springer-Verlag, New York, NY, 2002, 933-943.
12. Ekman, P. and Friesen, W. *The facial action coding system: A technique for the measurement of facial movement*. Palo Alto: Consulting Psychologists Press, 1978.
13. Elliot, A., and McGregor, H. A 2 x 2 achievement goal framework. *Journal of Personality and Social Psychology*, 80, 3, 501-519, 2001.
14. Gratch, J., and Marsella, S. A domain-independent framework for modeling emotion. *Journal of Cognitive Systems Research*, 5(4):269-306, 2004.
15. Johnson, L., and Rizzo, P. Politeness in tutoring dialogs: “run the factory, that’s what I’d do”. In *Proceedings of the 7th Intl Conf. on Intelligent Tutoring Systems*. Springer-Verlag, New York, NY, 2004, 67-76.
16. Kort, B., Reilly, R., & Picard, R. An affective model of interplay between emotions and learning: Reengineering educational pedagogy—building a learning companion. *Proceedings IEEE Intl. Conf. on Advanced Learning Technology: Issues, Achievements and Challenges* (pp. 43-48). Madison, WI: IEEE Computer Society, 2001.
17. Lips, H. (2007) *Sex and Gender: An Introduction*, 6th ed. McGraw-Hill.
18. McCrae, R., P. Costa (2003). *Personality in adulthood: A five-factor theory perspective* (2nd ed.). New York: Guilford Press.
19. McQuiggan, S., Lee, S., and Lester, J. (2007) Early prediction of student frustration. In *Proc. of the 2nd Intl. Conf. on Affective Computing and Intelligent Interaction*, Portugal.
20. McQuiggan, S., Robison, J., and Lester, J. (to appear) Affective transitions in narrative-centered learning environments. To appear in the *Proceedings of the 9th International Conference on Intelligent Tutoring Systems*, Montreal, Canada.
21. Paiva, A., Dias, J., Sobral, D., Aylett, R., Woods, S., Hall, L., and Zoll, C. Learning by feeling: Evoking empathy with synthetic characters. *Applied Artificial Intelligence*, 19:235-266, 2005.
22. Prendinger, H., and Ishizuka, M. The empathic companion: A character-based interface that addresses users’ affective states. *Applied Artificial Intelligence*, 19:267-285, 2005.
23. Rusting, C. (1998) Personality, mood, and cognitive processing of emotional information: three conceptual frameworks. *Psychological Bulletin*, 124(2):165-196.
24. Witmer, B., and Singer, M. Measuring presence in virtual environments: A presence questionnaire. *Presence: Teleoperators and Virtual Environments*, 7, 3 (1998), 225-240.