Antecedent-Consequent Relationships and Cyclical Patterns between Affective States and Problem Solving Outcomes

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Abstract. We explored the complex interplay between students’ affective states and problem solving outcomes. We conducted a study where 41 students solved 28 analytical reasoning problems from the Law School Admission Test. Participants viewed videos of their interaction history and judged their emotions at theoretically relevant points in the problem solving session (after new problem is displayed, in the midst of problem solving, after feedback is received). We explore excitatory and inhibitory relationships between the affective states and problem solving outcomes (i.e. success or failure, and associated positive or negative feedback). We isolate affective states that are consequences of outcomes and associated feedback as well as affective states that are antecedents of positive or negative outcomes. Follow-up analyses focused on cyclical patterns that incorporate complex relationships between the affective states and problem solving outcomes. Implications of our results for affect-sensitive artificial learning environments are discussed.

Keywords. affect, affective states, emotion, problem solving, intelligent tutoring systems, affect-sensitive, analytical reasoning, contradictory feedback, LSAT

Introduction

It is widely acknowledged that problem solving is an effective way to promote deep learning because it evokes a complex interplay of cognitive, affective, motivational, metacognitive, and meta-affective processes. Although the last four decades of research has provided valuable insights into the cognitive and motivational processes that underlie learning, relatively little is known about the influence of affective processes in modulating learning at deeper levels of comprehension. However, the affective link is critical because affective processes such as appraisal, expression, and regulation are inextricably bound to cognitive and metacognitive processes and have an impact on learning.

The importance of affect is further elevated in problem solving activities because solving problems in mathematics and science is inevitably accompanied by the natural steps of making mistakes and recovering from them. Failure and success in problem solving are accompanied by corresponding sets of negative and positive emotions.

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depending on the individuals’ affective traits, skills, knowledge, and goals. Simply put, the importance of emotions during problem solving cannot be underestimated because student affective states can impede or facilitate the problem solving process [1, 2], as well as engender different modes of thinking [3, 4].

Much of what is known about the influence of affect on effortful problem solving activities is limited to the effects of arousal and general moods on creative thinking and overall performance. For example, the Yerkes-Dodson classic law [5] proposes a curvilinear inverted U-shaped relationship between arousal and performance that varies by task demands. We also know that flexibility, creative thinking, and efficient decision-making have been linked to experiences of positive affect (e.g. [6]), while negative affect has been associated with a more methodical approach to assessing the problem and finding the solution [7].

However, there is reason to challenge the adequacy of basing an entire theory of affect and problem solving on arousal and mood states alone [4]. The relationship between positive and negative affective states and performance outcomes is more complex, and, in some cases counterintuitive. For example, although once widely acknowledged that positive moods enhances performance on creative problems [6], there is some evidence that it is the negative and not positive moods that have a beneficial impact on performance [1].

A narrow focus on general moods during problem solving runs the risk of overlooking the ebb and flow of dynamically changing affective states. It might be more informative to monitor the interactions between dynamic patterns of affect and problem solving outcomes than narrowly focusing on whether a learner is generally in a positive or negative mood while solving a problem.

Consequently, this paper explores the relationship between affect states and problem solving outcomes of 41 students who solved difficult analytical reasoning problems from the Law School Admission Test (LSAT). The LSAT was chosen as it is a difficult test that requires substantial cognitive resources and is expected to yield a rich set of affective experiences. In particular, we examine antecedent-consequent relationships between affective states and problem solving outcomes as well as complex affective-outcome cycles that span several states.

1. Methods

Participants were 41 undergraduate students from a southern college in the United States. The participants were selected from a population of students that were enrolled in a college program that offered practice testing for graduate school standardized tests.

Participants signed an informed consent before beginning the study. They interacted with a customized software program on a Tablet PC that delivered the questions, monitored their responses, and provided feedback (i.e. “Correct” or “Incorrect”). Effectively solving the analytical reasoning problems requires a considerable amount of knowledge representation, drawing diagrams, taking notes, and other related activities. Participants used a software application, Windows Journal™, to take notes and draw.

In order to expand the range of emotions that participants may experience while solving the LSAT problems, we experimentally manipulated the feedback provided to the participants. Feedback was manipulated so that incorrect feedback was randomly provided for 25% of the responses (i.e. providing negative feedback to correct
responses and vice versa). This form of deception was approved by the Institutional Review Board and participants were fully debriefed at the end of the experiment.

The experimenter left the room after demonstrating the software interfaces to the participants. They were told that they would be paid two dollars for each correct answer. All participants were paid $30. Each problem had a scenario and approximately 5-6 sub-questions pertaining to the scenario. Participants interacted with the system for approximately 35 minutes (the analytical reasoning section of the LSAT is 35 minutes long). During the interaction, videos of the participant’s face and computer screen were recorded.

Participants took part in a retrospective emotion judgment protocol [8, 9] after the problem solving phase. Participants were provided with a list of affective states with definitions. The list encompassed learning-centered cognitive-affective states (anxious, confusion, boredom, contempt, curiosity, eureka, frustration) [8-10], basic emotions (anger, disgust, fear, happiness, sadness, surprise) [11], and neutral (no emotion).

The procedure began by synchronizing and displaying the videos of the participant’s face and screen that were captured during the interaction. Participants were required to make affect judgments at theoretically relevant points in the session. These affect judgment points were: (a) Problem Onset - seven seconds after a new problem was displayed, (b) During Solution - halfway between the presentation of the problem and the submission of the response, and (c) After Feedback - three seconds after the feedback was provided. Both videos automatically paused at these affect judgment points where participants were required to make a judgment. In addition to the three pre-specified points, participants were able to manually pause the videos and provide affect judgments at any time.

2. Results and Discussion

Basic analyses (i.e. proportions of affect experienced, etc) on the affective experiences of students’ in the current study have been published elsewhere [12]. This paper focuses on more detailed analyses geared towards uncovering antecedent-consequent relationships between the affective states and problem solving outcomes. There were 14 affective states (see above) and four outcome categories: (a) PP = correct response + positive feedback, (b) NN = incorrect response + negative feedback, (c) PN = correct response + negative feedback, and (d) NP = incorrect response + positive feedback. Accurate feedback is provided for categories PP and NN (75% of the time) while contradictory feedback is provided for categories PN and NP (25% of the time). In the subsequent discussion affective states and outcome categories are simply referred to as states.

There were 2792 ($M = 68, SD = 19$) affect judgments from 41 learners. A time series that preserved the temporal ordering of affective states and outcome categories was constructed for each participant. We utilized the Likelihood metric (Eq. 1) [13] to characterize the antecedent-consequent relationships in each time series. The metric quantifies the likelihood that the current state ($C$) influences the next state ($X$) after correcting for the base rate of $X$. According to this metric, if $L(C \rightarrow X) \approx 1$, we can conclude that state $X$ reliably follows state $C$ above and beyond the prior probability of state $X$. If, on the other hand $L(C \rightarrow X) \approx 0$, then $X$ follows $C$ at the chance level. Furthermore, if $L(C \rightarrow X) < 0$, then the likelihood of state $X$ following state $C$ is much lower than the base rate of $X$. 

The likelihood of each transition was computed separately for each participant. One sample t-tests then assessed whether the transition was significantly greater than (excitatory), less than (inhibitory), or equal to zero (no relationship between antecedent and consequent). We assessed 306 transitions out of the possible landscape of 324 (18 × 18) transitions. Transitions between the same states were not included in the current analyses. Same state transitions focus on persistence properties which are not the focus of this paper and are addressed elsewhere [12].

It appears that there were 124 transitions that were statistically significant at the .05 level. 24 out of the 124 significant transitions were excitatory, while the remaining 100 were inhibitory. An additional 7 transitions (4 excitatory + 3 inhibitory) were marginally significant (i.e. \( p < .06 \)).

It should be noted that there is a risk of increasing Type 1 (false positive) errors when a large number of significance tests are conducted. One option to alleviate this risk is to focus on a small set of theoretically derived predictions instead of considering the entire set of potential transitions. This option was not considered because the primary goal of this study is to explore the broad landscape of affect and outcome dynamics with a discovery-oriented eye. Focusing on a small subset of transitions does not advance this goal. Another option is to make the significance criteria more stringent by applying the Bonferroni correction. This would result in an extremely small alpha value of \( .000163 \ ( .05/306) \). Using such a low alpha value is also not attractive as this substantially increases the risk of committing Type II (false negative) errors.

A closer examination of the number of significant transitions revealed that it is unlikely that our results were obtained by a mere capitalization on chance. Monte-Carlo simulations across 100,000 runs confirmed that the probability of obtaining 131 out of 306 significant transitions (43%) by chance alone is approximately 0. Additionally, the probability of obtaining 28 significant excitatory transitions by chance alone is also very minute (.01). Therefore, it is unlikely that the overall patterns in the data were obtained by chance.

A directed graph with the states as nodes and significant excitatory transitions as edges is presented in Figure 1. This graph was constructed on the basis of the 28 excitatory transitions alone because an examination of the 103 inhibitory transitions is beyond the scope of this paper. We begin with a discussion of simple two state antecedent-consequent relationships followed by more complex cyclical patterns that span several states.

2.1. Antecedent-Consequent Relationships among States

Several important findings pertaining to relationships between the affective states and the outcome categories emerge from Figure 1. It appears that some affective states are antecedents to the outcome variables while others are characteristic of consequential effects. Beginning with the affective states that are consequences of outcomes, it appears that providing incorrect responses and receiving true negative feedback (NN) spans a host of negative affective responses such as boredom, anger, disgust, frustration, and sadness. On the positive front, affective states such as eureka and
Figure 1. Directed graph representation of significant excitatory transitions. Circular nodes represent affective states. Diamond shaped nodes represent problem solving outcome states (i.e. combination of participant response and system feedback). PP = correct response + positive feedback, NN = incorrect response + negative feedback, PN = correct response + negative feedback, and NP = incorrect response + positive feedback.
happiness are experienced when a correct answer receives the expected positive feedback (PP). Providing positive feedback to an incorrect answer (NP) is met with the expected surprise. However, in addition to surprise, more visceral negative reactions such as frustration and sadness are evoked when a correct answer received negative feedback (PN).

Additional insights are obtained by shifting our focus to affective states that are antecedents to problem solving outcomes. It appears that boredom and curiosity share antithetical relationships with respect to how they influence problem-solving outcomes. Boredom inhibits performance while curiosity facilitates performance. Anxiety causes a form of performance paralysis with a negative impact that is similar to boredom. Additionally, as could be expected, the eureka experience positively facilitates problem solving. It is illuminating to note that frustration does not appear to have negative effects like boredom and anxiety, further substantiating the notion that it is boredom and not frustration that is the most detrimental to learning [10].

One interesting finding is that confusion is a predictor of both positive and negative outcomes. The positive link between confusion and performance substantiates several decades of research that highlight the importance of this emotion to problem solving and deep thinking [9, 14, 15]. Confusion is often accompanied by effortful cognitive activities as students try to problem solve and to arrive at a resolution (Confusion → PP link). But confusion also has a less attractive form, where learners are unable to achieve a resolution. This form of unresolved confusion is linked to negative outcomes (Confusion → NN link). Therefore, confusion seems to be the major gateway linking negative outcomes and their associated negative affective states with positive affective experiences and positive outcomes (left half versus right half of graph).

2.2. Cyclical Relationships among States

The aforementioned discussion focused on simple antecedent-consequent relationships between the affective states and problem solving outcomes. Additional insights can be gleaned by exploring more complex patterns of the directed graph depicted in Figure 1. One class of such patterns is routinely occurring cycles, which are sequences of states with the same start and end nodes. Routinely occurring cycles between the states might be diagnostic of repetitive patterns that are very relevant to modeling the interplay between the affective states and problem solving outcomes.

A cycle detection algorithm applied to the directed graph revealed 53 potential cycles. A sequence-matching algorithm was then used to compute the probability of each cycle occurring in each participant’s time series. The results indicated that only 20 of the 53 potential cycles occurred with non-zero probabilities. We then assessed which of these 20 cycles occurred at rates significantly greater than chance. The probability of a cycle occurring by chance was computed from a randomly shuffled surrogate of each participant’s time series. The metric depicted in Equation 2 was used to compute the likelihood of occurrence of each cycle.

\[
L(Cyc) = \frac{Pr\{Cycle \text{ in original time series} \} - Pr\{Cycle \text{ in shuffled time series} \}}{1-Pr\{Cycle \text{ in shuffled time series} \}} \quad \text{(Equation 2)}
\]

This metric can be interpreted in the same way as the metric presented in Eq. 1. One-tailed, one sample t-tests indicated that five cycles occurred at rates significantly
greater than chance. A one-tailed test was used because we are only testing cycles that are expected to occur above chance. Monte-Carlo simulations across 100,000 runs confirmed that the probability of obtaining 5 out of 20 significant cycles (25%) is very small (.04), therefore it is unlikely that our results were obtained by capitalizing on chance alone.

The five significant cycles are highlighted in Figure 1. It appears that bored students have the potential to get trapped in a vicious cycle of boredom, negative responses, and negative feedback (Cycle 1). Bored students disengage to an extent where any external stimulation is ineffective in alleviating their ennui. This pattern of boredom is consistent with previous research examining this state during tutorial sessions with three different ITSs [10].

In direct contrast to the vicious boredom-failure-boredom cycle, there is a virtuous cycle spawned by curiosity (Cycle 2). Curiosity is a state that is closely related to interest [16], and is a form of deliberate exploratory behavior [17] that leads to a correct response and the associated positive feedback and happiness. The happiness further excites curiosity and the positive cycle continues.

The consequences of confusion play an important role in the next three cycles. Confusion occurs when students experience impasses, salient contrasts, and other obstacles that block goals. Students attempt to alleviate their confusion by deliberation, problem solving, and other effortful cognitive activities. However, the outcome of these cognitive activities is uncertain; confusion can either be resolved or unresolved. Unresolved confusion leads to incorrect responses, negative feedback, and the inevitable frustration, and since the source of the confusion has not yet been resolved, the frustration eventually leads to more confusion (Cycle 3). However, an alternate cycle is activated when the source of confusion is resolved. This occurs when confusion is followed by a correct response, which receives positive feedback. The students’ confusion temporarily dissipates to neutral but it might recur as the problem solving process continues (Cycle 4).

Cycle 5 provides an interesting account of the impact of the feedback manipulation on the participants’ affective states. It appears that positive feedback being provided to confused students that submit incorrect responses temporarily alleviates their confusion, and students experience momentary happiness. This happiness has the potential of transitioning to curiosity, where students have the opportunity to enter the virtuous Cycle 2. However, if the usual negative feedback were provided instead of the contradictory positive feedback, then students’ would be likely to end up in the negative Cycle 3. Although highly suggestive at this point, there might be some merits to temporarily providing contradictory feedback to nudge students towards more positive cycles. Of course, the contradiction needs to be eventually resolved so that learning is not compromised.

3. Conclusions

Tutoring in mathematics and science routinely involves periods of unsupervised problem solving and the inevitable affective responses. Several next generation ITSs aspire to detect the learners’ affective states and respond with affect-sensitive pedagogical and motivational interventions. The research presented here can be used to scaffold the development of these affect-sensitive ITSs in two significant ways. First, the antecedent-consequent relationships can be leveraged to build predictive models of
learners’ affect that are aligned with problem solving outcomes. These predictive models can compliment systems that attempt to diagnose affective states by monitoring facial expressions, speech contours, and other bodily measures. Second, the cyclical models can be used to engineer affective interventions that promote transitions into virtuous cycles and proactively attempt to prevent transitions into vicious cycles. Our future research will investigate the extent to which individual differences in appraisals of failure and achievement goals [18] interact with the patterns observed in this paper. We hope that with further research such systems can help students conquer failure and its resultant negative emotions and resume with hope, determination, and even enthusiasm.

Acknowledgments

This research was supported by the U.S. Office of Naval Research (N00014-05-1-0241).

References