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Affect Dynamics Modeling

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Affect Dynamics Modeling
Gregory Moore

Interactive Qualifying Report completed in partial fulfillment
of the Bachelor of Science degree at
Worcester Polytechnic Institute, Worcester, MA

Submitted to: Professor Ryan Baker (advisor)

Gregory Moore

__________________________
(February 28, 2012)

Advisor Signature
Abstract

This project presents an analysis of the affect that precedes, follows, and co-occurs with the student behaviors of being off-task or being engaged in on-task conversation within two versions of a virtual chemistry laboratory. The analysis was conducted using field observation data collected in undergraduate classes using the virtual laboratory software as part of their regular chemistry classes. This analysis indicates that off-task behavior co-occurs with boredom but seems to lessen boredom, leading to a significantly lower probability of boredom later. The analysis also indicated that on-task conversation leads to a greater probability of future engaged concentration. These results help illuminate the role student behavior outside of education software plays in student affect during the use of the software.
Acknowledgements

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Executive Summary

The use of educational software is becoming ever more popular in the modern education systems. In this area, there has been lots of research on affect dynamics, or how affective states change or persist in a person over time. Most of this research has taken place in controlled laboratory settings. However, it is not clear if the results from these studies will also be seen in real world schools. The purpose of this research is to examine the dynamics of affective states and behaviors within the context of educational software in a real world classroom, so that the results may improve the effectiveness of future educational software and further develop the model of affect dynamics. These dynamics are measured by examining affective states transitioning into behaviors, behaviors transitioning into affective states, and the co-occurrences of affective states and behaviors.

This was done by observing undergraduate students using a piece of educational software. In this case, the educational software was a chemistry virtual laboratory. During use of the software, the observers recorded student behavior and affective states. The behaviors included Off-Task behavior, On-Task Behavior, On-Task Conversation, and Gaming the System. The affective states included boredom, engaged concentration, confusion, and frustration. This data was then analyzed by examining the prevalence of each behavior and affect, and by using a transition metric $L$. This value indicates how likely a transition or co-occurrence between an affective state and behavior is to occur.

The results indicated that on-task behavior was the most prevalent behavior and engaged concentration was the most prevalent affective state. Gaming the system was very uncommon, comprising of less 0.1% of all observations. In terms of transitions and co-occurrences, a few
interesting results were found. The first main finding was that an off-task student was not likely to be bored in the next observation even though off-task behavior and boredom are likely to co-occur. This indicates that off-task behavior may disrupt bored behavior and help get the student back on track. Secondly, students who were frustrated were less likely to go off-task and frustration and off-task behavior were unlikely to co-occur. Finally, the affective states of engaged concentration and confusion were unlikely to co-occur with off-task behavior.

The results suggest that off-task behavior may actually be beneficial, as it acts as a positive emotion self-regulation strategy. This is due to the fact that off-task behavior may interrupt vicious cycles of negative affect, such as boredom and frustration. When the negative affect is disrupted, it allows the student to get back on task and begin engaging with the learning material again. The results also suggest that if a student talks to someone else, such as a teacher or student, about their problems or confusions, they will be less likely to be frustrated in the future. Therefore, the results suggest that the relationship between behavior and affect is more complicated than previously though. Future research should examine the effect off-task behavior and on-task conversation more closely. If a better understanding of these relationships is found, future learning environments could use this information to better help students learn.
Introduction / Literature Review

In recent years, there has been an increasing interest in studying the dynamics of affective states and behaviors, as well as the interplay between affect and behavior, within the contexts of human-computer interaction. More specifically, the recent research has investigated affective dynamics, and the dynamics between affect and behavior, within the context of students using educational software.

Early theoretical work has been done in this area. Kort, Reilly, and Picard (Kort, Reilly, & Picard, 2001) produced a set of hypotheses for transitions between affective states. These hypotheses were based upon Piagetian theories of cognitive equilibrium and disequilibrium. D’Mello, Taylor, and Graesser (2007) found that few transitions between states occur significantly more or less than chance when they conducted a fine-grained analysis on student affect with educational software in a laboratory setting. However, they did find some evidence that some affective states were significantly more like to persist over time than others. Specifically, their results provided evidence for a vicious cycle of boredom, and a virtuous cycle of flow (flow was renamed “engaged concentration” in later work (Baker et al., 2010)). This finding was later replicated in classroom settings (Baker et al., 2010) in the Philippines. Later analysis, where persistence of the same affective state was eliminated from the analysis, found evidence that transitions from confusion to frustration are common. These analyses also found that frustration might lead to several different affective patterns, including alleviated frustration, frustration alternating with confusion, and frustration leading into boredom (D’Mello & Graesser, 2010). It has also been found that altering interactive learning environments to display empathy can disrupt vicious cycle of boredom and frustration (McQuiggan, Robison, & Lester, 2010). However, not all types of motivational messages have this effect (Rodrigo et al., 2008).
This research has also been extended to study the interplay between affect and specific behaviors associated with differences in learning outcomes. Two studies on affect and behavior dynamics were conducted with high school students using an intelligent tutor or an educational game (Baker et al., 2010) in the Philippines. For both of these studies, the analyses indicated that boredom was likely to be followed by gaming the system (Baker et al., 2004). Gaming the system is a behavior in which students systematically guess or exploit help in the software in order to obtain answers without thinking through the learning material. However, it is unknown if these findings will be able to be generalized to United States classrooms, because social patterns differ between the Philippines and the United States. It was also reported that off-task behavior leads to different affective consequences, depending on whether the off-task behavior followed confusion or frustration (Sabourin et al., 2011). Confusion that led to off-task behavior tended to lead to frustration or boredom, whereas frustration followed by off-task behavior tended to lead to positive engagement.

Other research on the relationship between affective states and behavior in educational contexts has typically been conducted at coarser-grained levels, meaning that self-report was often used to measure the overall prevalence of affect behavior rather than looking at transition over seconds or minutes. For example, Pekrun et al. (2010) found that boredom was positively associated with attention problems in undergraduate students and that boredom was negatively associated with the use of elaboration and self-regulation techniques. Nottelman and Hill (1977) examined the relationship between anxiety and off-task behavior during high-stakes testing, for which they found a positive correlation. Larson and Richards (Larson & Richards, 1991) reported that a student’s overall frequency of boredom in school was not statistically significantly correlated with their overall incidence of disruptive behavior.
In this study, the interplay between student affective states and two forms of student behavior among students learning from educational software are being investigated. These two behaviors are off-task behavior and on-task conversation. Off-task behavior is defined as any behavior that does not involve the learning software or its domain in any way. It often stems from attentional difficulties, such as those studied by Pekrun et al. (2010). On-task conversation is defined as talking to another student or the instructor about the educational software or its domain, rather than solely interacting with the software.

These two behaviors are distinguished from other forms of behavior during learning from educational software in that these two behaviors occur outside of the software, even though they may make a significant impact on learning from the software. An analysis of these behaviors will help expand the understanding of the overall process of learning educational software. This includes students’ behavior and learning processes in the human-computer interaction between student and the software, as well as behavior and learning processes in the social interactions surrounding the use of the software (Schofield, 1995). Both of these behaviors also occupy significant amounts of student time during use of educational software (Schofield, 1995). For example, one study found that students learning middle school mathematics from educational software spent 19% of the time engaging in these behaviors (Baker et al., 2004). However, there are some important differences in these two behaviors.

Engaging in off-task behavior is, by definition, not learning. Off-task behavior has also repeatedly been shown to associate with poorer learning outcomes during individual learning (Karweit & Slavin, 1982; Lahaderne, 1968; Lee, Kelly, & Nyre, 1999), including in educational software (Baker et al., 2004). Off-task behavior is also often early indicator of more serious
forms of disengagement, such as skipping class or dropping out of school (Finn, 1989; Tobin & Sugai, 1999).

On the other hand, on-task conversation plays a substantial and positive role in learning from educational software. On-task conversation has even been observed in software designed for individual use when it was used in a classroom setting (Baker et al., 2004; Schofield, 1995). Several type of on-task conversation have been noted (Schofield, 1995): students collaborating on learning difficult material, students seeking help from an instructor, and instructors spontaneously providing help to a struggling student.

With the study of what affect precedes or co-occurs with these two categories of behavior during learning, a better theoretical understanding of how affect influences outcomes in real world tasks could emerge. In addition to this, the understanding of how behavior outside of the human-computer interaction is driven by affect occurring during the human-computer interaction and how this, in turn, shapes the later affect when the student is again focused on interacting with the computer may be enriched.
Methodology

Software Used

For these analyses, first-year undergraduate chemistry classes were observed using a virtual chemistry laboratory software (as seen in Figure 1) (Yaron et al, 2010). This software allows students to design and carry out their own experiments by retrieving chemical solutions from a virtual stockroom (found in the left panels of Figure 1), and then manipulating these solutions using standard glassware and equipment such as Bunsen burners, pH meter, and balances (central panels). The right panels in Figure 1 provide information on the contents of the selected solution, including the temperature, pH, and a list of chemical species and their concentrations. Past research on this learning environment suggests that having students design and carry out their own experiments involves a deeper level of understanding of chemical phenomena than solving standard text-based problems. This approach allows students to move beyond shallow problem solving strategies (Yaron et al., 2010), a finding also seen with other virtual laboratory software (Sao Pedro, Gobert, & Raziuddin, 2010).

For the purposes of this research, the students were observed determining the identity and concentration of an acid in an unknown solution, using a procedure known as titration. There were two variants of this activity: a game mode and a non-game mode. In the non-game mode (top of Figure 1) of the virtual chemistry laboratory, students worked in pairs to identify the unknown solutions and enter their answers into a web form that checked for accuracy. The laboratory allowed three incorrect attempts before issuing a new unknown chemical solution, to discourage guessing. The game mode (bottom of Figure 1) involved students creating an unknown solution for their opponent. The first student to determine the contents of the other student’s created solution won the game. In addition to the competition, this mode also involved
the additional strategies of finding what chemical solution would be most difficult for the opponent to identify and determining the quickest way to identify the contents of the unknown solution.

![Image](image.png)

**Fig. 1.** The virtual laboratory for chemistry (top window represents the original version; bottom window represents the game version)

**Data Collection Method**

Student behavior was coded as they used the two versions of the virtual laboratory, both the game and non-game versions, by two expert coders. These coders used software on a Google Android handheld computer, which implemented an observation protocol developed specifically for the process of coding behavior and affect during use of educational software
(Baker et al., 2010). The two coders had been trained previously in coding behavior and affect by this project’s advisor. The first coder achieved an inter-rater reliability with the advisor of 0.83 and the second coder achieved an inter-rater reliability with the advisor of 0.72 in previous research conducted with students using other learning environments. This reliability is on par with kappas reported by past projects which have assessed the reliability of detecting naturally occurring emotional expressions (Baker et al., 2010; Bartel & Saavedra, 2000; Litman & Forbes-Riley, 2004; Rodrigo et al., 2008).

Each observation lasted up to twenty seconds, with observation time so noted by the handheld observation software. If affect and behavior were determined before twenty seconds elapsed, the coder moved to the next observation. All of the observations were conducted using peripheral vision. The observers stood diagonally behind the student being observed and avoided looking at the student directly (Baker et al., 2010; Baker et al., 2004; Rodrigo et al., 2008). This was done to make it less clear to the students when observations were being done, so that they would not alter their behavior. This method had previously been found to be highly successful for assessing student behavior and affect, achieving good inter-rater reliability (Baker et al, 2010; Baker, Corbett, & Wagner, 2006; Rodrigo et al., 2008). To simplify the encoding and analysis processes, if two distinct affect states or behavior were seen during one observation, only the first state or behavior observed was coded.

Affective states and behaviors were based on the student’s work context, actions, utterances, facial expressions, body language, and interactions with teachers and fellow students, which are broadly the same types of information used in previous methods for coding affect (Bartel & Saavedra, 2000). It is also in line with Planalp et al’s (1996) descriptive research on
how humans generally identify affect using multiple cues together for maximum accuracy rather than attempting to select individual cues.

Within each observation, each observer coded affect with references to five categories: Boredom, Confusion, Engaged Concentration, Frustration, and a catch-all category that included any affective state other than those four. Each observer coded a behavior as well, also in five categories: Gaming the System, Off-Task, On-Task Solitary, On-Task Conversation, and a catch-all category. The catch-all categories also include indeterminate behavior and cases where affective coding is impossible, such as if the student left the room. These classifications were based on the affective states and behaviors used in a previous study (Baker et al., 2010).

During the observation period, 700 observations were recorded across the students, with an average of 13.0 observations per student. Of the 700 observations, 46 behaviors were coded as “?”, and 90 affective states were coded as “?”. These observations were not analyzed, but were retained sequences for transition analysis. An average of 131.7 seconds passed between observations.

Subjects

The observations were conducted in a computer laboratory at a private university in a city in the Northeastern United State, where 55 students used the Virtual Laboratory software as part of their regular undergraduate chemistry class. The activity lasted approximately 45 minutes with the students randomly assigned to the two conditions. Two classes sections of students used the software, with students randomly assigned within class, so that each class had students in both conditions. Before the class began, an ordering of observation was chosen based on the computer laboratory’s layout, and was enforced using the hand-held observation software.
Results and Discussion / Analysis

Prevalence of Each Behavior

Of the four behaviors possible for students, On-Task Solitary behavior was by far the most common for students to be engaged in, with students engaging in On-Task Solitary behavior 71.6% of the time. On-Task Conversation was the next most common, with students engaging in it 22.2% of the time. Off-task was less prevalent than that, with students engaging in Off-task behavior 6.3% of the time, and Gaming the system was very uncommon, accounting for less than 0.1% of all recorded student behaviors. These results are summarized below in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Gaming the System</th>
<th>Off-Task</th>
<th>On-Task Solitary</th>
<th>On-Task Conversation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevalence</td>
<td>&lt;0.1%</td>
<td>6.3%</td>
<td>71.6%</td>
<td>22.2%</td>
</tr>
</tbody>
</table>

Table 1. Prevalence of each student behavior in the sample (averaged within students and then averaged across students). Observations labeled “?” are excluded from analysis.

Prevalence of Each Affect

Of the four affects possible, Engaged Concentration was the most prevalent for the students to be engaged in. Engaged Concentration accounted for 81.6% of the affect observations. Confusion was the next most prevalent affect observed, with 14.1% of the observations, followed by Frustration, with 2.5% of the observations. Boredom was the least prevalent affective state and was observed 1.9% of the time. These results are summarized in Table 2.
There were no significant differences in the prevalence of any behavior or affective state between the two Chemistry Virtual Laboratory Environments. For this reason, the two environments will be considered together for the remaining analyses.

D’Mello et al.’s transition metric

Transitions and co-occurrence between affect and behavior were studied using D’Mello et al.’s transition metric, $L$ (D’Mello, Taylor, & Graesser, 2007). This metric provides the probability of a transition or co-occurrence happening above or below the base rate of each affective state or behavior. For example, On-Task Solitary behavior occurs in 71.6% of all observations. This means that On-Task Solitary behavior is the most likely behavior to follow or co-occur with any affective state observed. The $L$ metric explicitly accounts for the base rate probability of each behavior and affective state occurring when assessing how likely a transition or co-occurrence is, given the probability that a transition/co-occurrence between two states occurs and the base frequency of the destination state.

For $L$, a value of 1 indicates that the transition or co-occurrence will always occur, whereas a value of 0 indicates that the likelihood of the transition/co-occurrence occurring is no different that the probability of the destination state occurring. $L$ values above 0 signify that the transition or co-occurrence is more probable than the base frequency of the destination state.

<table>
<thead>
<tr>
<th></th>
<th>Engaged Concentration</th>
<th>Confusion</th>
<th>Frustration</th>
<th>Boredom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevalence</td>
<td>81.6%</td>
<td>14.1%</td>
<td>2.5%</td>
<td>1.9%</td>
</tr>
</tbody>
</table>

Table 2. Prevalence of each affective state in the sample (averaged within students and then averaged across students). Observations labeled “?” are excluded from analysis.
whereas a value below 0 indicates that the transition or co-occurrence is less probable than the base frequency of the destination state.

The $L$ calculation is shown below in Equation 1.

$$L = \frac{\Pr(\text{Next}|\text{Prev}) - \Pr(\text{Next})}{1 - \Pr(\text{Next})}$$

Equation 1

For each transition or co-occurrence, an $L$ value was calculated for each student in the data set. Then, the mean and standard deviation of the $L$ values for all students in a transition or co-occurrence was calculated. Once these values were calculated, it could be determined if a given transition/co-occurrence was more likely than chance using a two-tailed t-test for one sample. Students who never displayed the previous behavior or affective state for a given transition gave no evidence on transitions from that affective state or behavior, and were therefore not included in the $L$ calculation. Likewise, it was not possible to calculate transition likelihood for students who always displayed the same following affective state or behavior, and were also not included in the $L$ calculation.

Transitions and Co-occurrences of Behavior and Affect

There was an interesting relationship between boredom and off-task behavior. Boredom and off-task behavior often co-occurred, $t(26) = 2.58$, two-tailed $p = 0.02$. However, a bored student was not be more likely to go off-task in the next observation, $t(11) = -0.63$, two-tailed $p = 0.54$. Surprisingly though, an off-task student was less likely to be bored in the next observation, $t(23) = -3.05$. This indicates that off-task behavior relieves boredom. Furthermore,
this suggests that off-task behavior may be beneficial in that it disrupts “vicious cycles” of boredom (Baker et al., 2010; D’Mello, Taylor, Graesser, 2007).

The other interesting relationship discovered in these analyses was between the frustration affect and off-task behavior. Frustrated students were marginally less likely to go off-task in the next observation, \( t(11) = -2.03, \text{ two-tailed } p = 0.07 \). Off-task behavior and frustration were also less likely than chance to co-occur, \( t(26) = -2.06, \text{ two-tailed } p=0.05 \). There was not a statistically significant relationship between off-task behavior and future frustration, \( t(23) = 1.51, \text{ two-tailed } p = 0.15 \).

None of the other affective states were more or less likely than chance to precede or follow off-task behavior. However, the affective states of engaged concentration and confusion were significantly less likely when a student was off task; \( t(26) = -5.35, \text{ two-tailed } p <0.001 \) for the engaged concentration and off-task co-occurrence and \( t(26) = -3.49, \text{ two-tailed } p < 0.01 \) for the confusion and off-task co-occurrence.

On-task conversation was not significantly preceded by any affective states. However, it was significantly less likely than chance to precede frustration, \( t(42) = -2.11, \text{ two-tailed } p = 0.04 \). This indicates that on-task conversation with another person resolves problems that may cause future frustration.

For co-occurrence, students were significantly more likely than chance to be confused while engaging in on-task conversation, \( t(43) = 3.92, \text{ two-tailed } p < 0.001 \). Students were also significantly less likely than chance to be bored while engaging in on-task conversation, \( t(43) = -2.92, \text{ two-tailed } p = 0.01 \). They were also significantly less likely to be in engaged concentration
while in on-task conversation, t(36) = -2.02, two-tailed p = 0.05. This may indicate that confused students might seek help, increasing the likelihood of being on-task and talking to another person, while bored or concentrating students may not require help, and therefore not engage in on-task conversation. There was not a significant co-occurrence between on-task conversation and frustration, t(43) = 1.10, two-tailed p = 0.28. The summary of transitions and co-occurrences are included in Table 3 below.

| Off Task → Bored  | -0.04 (0.06) | Off Task → Confused | -0.04 (0.29) |
| Off Task → Eng. Conc. | -0.20 (1.54) | Off Task → Frustrated | 0.07 (0.24) |
| OnTask Conv → Bored | -0.01 (0.06) | OnTask Conv → Confused | 0.02 (0.27) |
| OnTask Conv → Eng. Conc. | 0.10 (0.94) | OnTask Conv → Frustrated | -0.01 (0.04) |
| Bored → Off Task | -0.03 (0.16) | Confused → Off Task | -0.03 (0.14) |
| Eng. Conc. → Off Task | 0.00 (0.10) | Frustrated → Off Task | -0.04 (0.07) |
| Bored → OnTask Conv | 0.11 (0.66) | Confused → OnTask Conv | 0.07 (0.54) |
| Eng. Conc. → OnTask Conv | -0.05 (0.26) | Frustrated → OnTask Conv | -0.05 (0.39) |
| Off Task → Bored | 0.19 (0.37) | Off Task → Confused | -0.18 (0.26) |
| Off Task → Eng. Conc. | -1.75 (1.67) | Off Task → Frustrated | -0.02 (0.06) |
| OnTask Conv → Bored | -0.02 (0.05) | OnTask Conv → Confused | 0.19 (0.32) |
| OnTask Conv → Eng. Conc. | -0.78 (2.30) | OnTask Conv → Frustrated | 0.02 (0.10) |

Table 3. Base-rate adjusted likelihood (average D’Mello’s L across students) and standard deviation (in parentheses) of each behavior-affect transition (denoted by arrow) or co-occurrence (denoted by dash-dash) within the data set. Statistically significant transitions (p<0.05) in boldface; marginally significant transitions (p<0.1) in italics.
Conclusions and Recommendations

This research examined the relationship between affective states and behavior in two ways. First, it examined how behaviors and affective states co-occur with each other. Second, it examined how behaviors transitioned into affective states and how affective states transitioned into behaviors. Specifically this paper examines how two specific behaviors (off-task behavior and on-task conversation) related to different affective states. All of these analyses were carried out on field observation data from undergraduates using virtual laboratory software for chemistry.

The most noteworthy finding was that off-task behavior co-occurs with boredom, but that boredom is significantly less likely than chance following off-task behavior. This interesting dynamic of boredom and off-task behavior seen here may explain why past research found that the overall prevalence of boredom does not significantly correlate with the overall frequency of extreme forms of off-task behavior (Larson & Richards, 1991). Past theories of off-task behavior have frequently focused on its negative correlates, such as poorer learning (Baker et al., 2004; Karweit & Slavin, 1982; Lahaderne, 1968; Lee, Kelly, & Nyre, 1999), and skipping school and dropping out (Finn, 1989; Tobin & Sugai, 1999). However, this research seems to suggest that off-task behavior is a necessary part of keeping students motivated and interested, as the off-task behavior seems to help disrupt the “vicious cycles” of boredom, where a student who is bored is likely to remain bored (Baker et al., 2010; D’Mello, Taylor, Graesser, 2007). Similar results were found in another study (Sabourin et al., 2011) where frustrated students who go off-task were seen to demonstrate future engagement. Therefore, it seems as if reasonable amounts of off-task behavior may benefit affect and overall learning. This finding matches up with work
by Kreijns (Kreijns, 2004) which suggests improved relationships, and collaboration, between students due to off-task behavior.

Another interesting result from this research was the relationships between on-task conversation and affect. Specifically, this research suggests that on-task conversation is associated with less future probability of frustration. These results confirm earlier reports stating that on-task conversation is a normal part of “individual” learning in classrooms (Baker et al., 2004; Schofield, 1995). Furthermore, the reports also suggest that collaborative episodes during individual learning often lead to the types of affect that are associated with successful learning. Future research might want to examine what the affective impacts are of periods of individual work during collaborative learning.

Overall, the results from these analyses suggest a more complex interplay between affective states and behaviors in education settings than previously thought. Further research may want to conduct a finer grain analysis of the effects of off-task behavior during learning, as well as the factors leading to and effects of on-task collaboration. With an understanding of these relationships, future learning environment could be designed to better leverage the positive aspects of off-task behavior and on-task conversation, while minimizing their negative aspects.
References


