The Dynamics Between Student Affect and Behavior Occurring Outside of Educational Software

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Abstract. We present an analysis of the affect that precedes, follows, and co-occurs with students' choices to go off-task or engage in on-task conversation within two versions of a virtual laboratory for chemistry. This analysis is conducted using field observation data collected within undergraduate classes using the virtual laboratory software as part of their regular chemistry classes. We find that off-task behavior co-occurs with boredom, but appears to relieve boredom, leading to significantly lower probability of later boredom. We also find that on-task conversation leads to greater future probability of engaged concentration. These results help to clarify the role that behavior outside of educational software plays in students' affect during use of that software.

Keywords: Affect dynamics, off-task behavior, virtual laboratory

1 Introduction

In recent years, there has been increasing interest in studying the dynamics of affect, and the interplay between affect and behavior, within real-life contexts of human-computer interaction. In specific, considerable recent research has investigated affective dynamics, and the dynamics between affect and behavior, within the context of students using educational software. In early theoretical work in this area, Kort, Reilly, and Picard [9] produced a set of hypotheses for the transitions between affective states, based on Piagetian theories of cognitive equilibrium and disequilibrium. D'Mello, Taylor, and Graesser [6] conducted fine-grained analysis on student affect within educational software in a laboratory setting and found that few transitions between states occur significantly more or less than chance. However, they found evidence that some affective states were significantly more likely to have self-transitions (e.g. persistence over time) than others. In specific, their results provided evidence for a vicious cycle of boredom, and a virtuous cycle of flow (renamed "engaged concentration" in later work [e.g. 1]). This finding was replicated in classroom settings in [1]. Later analysis where self-transitions were eliminated from analysis found evidence that transitions from confusion to frustration are common, but also found that frustration may lead to several different affective patterns, including alleviated frustration, frustration alternating with confusion, and frustration leading into boredom [5]. It has also been found that altering interactive learning environments to display empathy can disrupt vicious cycles of boredom and frustration [15], although not all types of motivational messages have this effect [19].

Researchers have also extended research on affective dynamics, to study the interplay between affect and specific behaviors associated with differences in learning outcomes, at a fine-grained level. In [1], two studies on affect-behavior dynamics were conducted for high school students using an intelligent tutor or an educational game in class. In both studies, analysis was presented showing that student boredom was likely to be followed by gaming the system [cf. 3], a behavior where students engage in systematic guessing or rapid help requests to obtain answers without thinking through the learning material. In [20], it was reported that off-task behavior leads to different affective consequences, depending on whether off-task behavior follows confusion or frustration; confusion followed by off-task behavior leads to frustration or boredom, whereas frustration followed by off-task behavior leads to positive engagement. Other research on the relationships between affect and behavior in similar educational contexts has typically been conducted at a coarser-grained level (e.g. self-report of overall prevalence of affect and behavior rather than transitions over seconds or minutes). For instance, Pekrun et al. [17] found that boredom was positively associated with attention problems in undergraduate students, and negatively associated with the use of elaboration and self-regulation strategies. Nottelmann and Hill [16] analyzed the relationship between anxiety and off-task behavior during high-stakes testing, finding a positive correlation. Larson and Richards [12] found that a student's overall frequency of boredom in school was not statistically significantly correlated to their overall incidence of disruptive behavior (considered an extreme form of off-task behavior) as reported by their teacher.

Within the current study, we investigate the interplay between student affect and two forms of student behavior among students learning from educational software: off-task behavior, and on-task conversation (defined below). These behaviors are distinguished from other forms of behavior during learning from educational software in that these behaviors occur outside the software, even though they may have significant impact on learning from the software. Analyzing these behaviors helps to expand our understanding of the overall process of learning from educational software, which includes student behavior and learning processes in the human-computer interaction between the student and the software, as well as behavior and learning processes in the social interactions surrounding the use of the software [cf. 22].

Off-task behavior consists of behaviors that do not involve the learning software or its domain in any way, and often stems from the types of attentional difficulties studied by Pekrun et al. [17]. On-task conversation consists of talking to another student or the instructor about the educational software or its domain, rather than interacting solely with the educational software. Both of these behaviors pertain to what the student does beyond just interacting with the educational software. Both behaviors also occupy significant amounts of student time during use of educational software [22]. For instance, [3] found that students learning from educational software in middle school mathematics classes spent 19% of the time engaging in these behaviors. However, there are some important differences between these behaviors.

Time spent engaging in off-task behavior is (by definition) time not spent learning, and off-task behavior has been repeatedly shown to be associated with poorer learning outcomes during individual learning [cf. 8, 11, 13], including within educational software [3]. In addition, off-task behavior is often an early harbinger of more serious forms of disengagement, such as skipping class or dropping out of high school [7, 23].

By contrast, on-task conversation plays a substantial and positive role in learning from educational software. On-task conversation has been observed even in software designed for individual use, when that software is used in classroom settings [e.g. 3, 22]. Several types of on-task conversation have been noted [22]: students collaborating on learning difficult material; students seeking help from the instructor; and instructors spontaneously providing help to a struggling student.

By studying what affect precedes these two categories of behavior during learning, and what affect accompanies the behaviors' emergence, we can improve the theoretical understanding of how affect influences outcomes during real-world tasks. We can also enrich our understanding of how behavior outside of the human-computer interaction is driven by affect occurring during the human-computer interaction, and in turn how this shapes later affect when the student is again focused on interacting with the computer.

2 Data Collection and Data Labeling

This paper examines students in first-year undergraduate chemistry classes using virtual laboratory software (Fig. 1) [24]. The software allows students to design and carry out their own experiments by retrieving chemical solutions from the stockroom (left panels of Fig. 1), and manipulating these solutions using standard glassware and equipment such as Bunsen burners, pH meters and balances (center panels). The right panels provide information on several properties of the contents of the selected solution, including the temperature, pH, and a list of chemical species and their concentrations (the list of species is not available for activities involving identification of unknowns, such as those considered here). Past research on this virtual learning environment suggests that having students design and carry out experiments involves a deeper level of understanding of chemical phenomena than solving standard text-based problems This helps students move beyond shallow problem-solving strategies [24], a finding also seen with other virtual laboratories and in other populations [e.g. 21].

In the activities considered here, students must determine both the identity (HCl, HF, etc) and concentration of an acid in an unknown solution, using a procedure known as titration. Students used two variants of this activity. In the non-game mode of the virtual laboratory (Fig. 1 top), students worked in pairs to identify unknown solutions and enter their answers into a web form that checked for accuracy and allowed three incorrect attempts before issuing a new unknown chemical solution. In the game mode of the virtual laboratory studied in this paper (Fig. 1 bottom), students first created an unknown solution for their opponent. The first student to determine

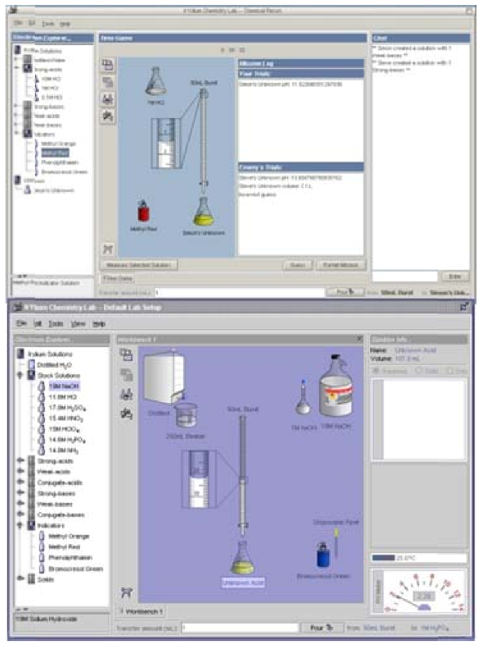

Fig. 1. The virtual laboratory for chemistry (top window represents the original version; bottom window represents the game version)

the contents of the unknown created by their opponent won the game. In addition to competition, the game mode brings in the additional strategies of determining what chemical solution would be most difficult for an opponent to identify, and determining the procedure that would most quickly identify the contents of an unknown.

Student behavior was coded as they used both versions of the virtual laboratory, by a pair of expert coders. The 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, replicating the protocol in [1]. All coding was conducted by the third and fourth authors. These two coders were previously trained in coding behavior and affect by the first author and have achieved inter-rater reliability with the first author of 0.83 (first and third authors, behavior [cf. 2]) and 0.72 (first and fourth authors, affect) in previous research conducted with students using other learning environments. This degree of reliability is on par with kappas reported by past projects which have assessed the reliability of detecting naturally occurring emotional expressions [1, 4, 14, 19].

Observations were conducted in a computer laboratory at a private university in a city in the Northeastern United States, where 55 students used the Virtual Laboratory software as part of their regular undergraduate chemistry class. The activity lasted approximately 45 minutes, with students randomly assigned to the two conditions. Two class sections of students used the software, with students randomly assigned within class (i.e., each class had students in each condition). 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.

Each observation lasted up to twenty seconds, with observation time so far noted by the hand-held observation software. If affect and behavior were determined before twenty seconds elapsed, the coder moved to the next observation. Each observation was conducted using peripheral vision or side glances. That is, the observers stood diagonally behind the student being observed and avoided looking at the student directly [cf. 1, 3, 19], in order to make it less clear when an observation was occurring. This method of observing using peripheral vision was previously found to be highly successful for assessing student behavior and affect, achieving good inter-rater reliability [1, 2, 19]. To increase tractability of both coding and eventual analysis, if two distinct affective states were seen during a single observation, only the first state observed was coded. Similarly, if two distinct behaviors were seen during a single observation, only the first behavior observed was coded. Any behavior or affect of a student other than the student currently being observed was not coded.

The observers based their judgment of a student's state or behavior on the student's work context, actions, utterances, facial expressions, body language, and interactions with teachers or fellow students. These are, broadly, the same types of information used in previous methods for coding affect [e.g. 4], and in line with Planalp et al's [18] descriptive research on how humans generally identify affect using multiple cues in concert for maximum accuracy rather than attempting to select individual cues. The judgments of behavior and affect were based on a sub-set of the coding scheme used in [1]. Within an observation, each observer coded affect with reference to five categories: boredom, confusion, engaged concentration (the affect associated with the flow state [cf. 1]), frustration, and "?", which refers to any affect outside the coding scheme, including eureka, delight, and surprise. "?" also includes indeterminate behavior and cases where it was impossible to code affect, such as when a student went to the bathroom or the software crashed. Delight and surprise were removed from the earlier coding scheme due to the relative rarity of these affective states in prior research [e.g. 1, 6, 19]. Each observer coded behavior with reference to five categories: on-task solitary behavior, on-task conversation, off-task behavior, gaming the system, and "?". Working silently in the game was coded as on- task solitary behavior, even though the student was competing with another student.

During the period of observation, 700 observations were conducted across the students, at an average of 13.0 observations per student. Of the 700 observations, 46 behaviors were coded as "?", and 90 affective states were coded as "?". Observations labeled in this way were not analyzed, but were retained in sequences (e.g., in a sequence of three observations where observation two was coded "?", observation three was not considered to be immediately after observation one). An average of 131.7 seconds passed between observations.

3 Analysis and Results

3.1 Overall Frequency of Behaviors and Affective States

The frequency of each behavior coded, averaged within each student and then averaged across students, is given in Table 1. As can be seen, gaming was quite rare across students, occurring under 0.1% of the time. In fact, only one observation was noted as involving gaming the system, possibly due to the exploratory nature of the virtual laboratory, and the high cost of making errors in the game. Off-task behavior was also relatively uncommon within this population, occurring 6.3% of the time. However, on-task collaboration was quite common, accounting for 22.2% of student behavior. On-task solitary behavior accounted for 71.6% of student behavior.

The frequency of each affective state, averaged within each student and then averaged across students, is given in Table 2. The most common affective state was engaged concentration, occurring 81.6% of the time. The second most common affective state was confusion, occurring 14.1% of the time. Frustration and boredom were each relatively uncommon, respectively occurring 2.5% and 1.9% of the time. The relative frequency of engaged concentration and confusion is consistent with past reports of the prevalence of affect during use of educational software across settings (laboratory and classroom), populations (undergraduate, high school, middle school), and educational software package [1, 5, 6, 15, 19], although frustration and boredom were less common than has been reported in these earlier studies. The lower incidence of these affective states and off-task behavior, compared to previous studies, is likely not due to observer effects, since many past studies of these constructs had similar numbers of observers and similar observation protocols.

There were no significant differences in the prevalence of any affective state or behavior between the two environments. As such, data from the two environments will be considered together throughout the remainder of the paper.

3.2 Transitions and Co-Occurrences of Behaviors and Affective States

The transitions between affect and behavior, and co-occurrence between affect and behavior, were studied using D'Mello et al.'s [6] transition metric, ***L***. ***L*** provides an indication of the probability of a transition or co-occurrence above and beyond the base rate of each affective category or behavior. For instance, on-task solitary behavior was the most common behavior in the Chemistry Virtual Lab; therefore, this behavior is likely to be the most common behavior that follows or co-occurs with *any* affective state in these environments. ***L*** explicitly accounts for the base rate of each state when assessing how likely a transition is, given the probability that a transition between two states occurs, and given the base frequency of the destination state. ***L*** is computed as shown in equation 1:

$$L = \frac{\Pr(Next|Prev) - \Pr(Next)}{1 - \Pr(Next)} \qquad \textbf{Equation 1}$$

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

	Gaming the System	Off-Task	On-Task Solitary	On-Task Conversation
Prevalence	<0.1%	6.3%	71.6%	22.2%

Table 2. Prevalence of each affective state in the sample (averaged within students and then averaged across students). Observations labeled "?" are excluded from analysis.

	Engaged Concentration	Confusion	Frustration	Boredom
Prevalence	81.6%	14.1%	2.5%	1.9%

A value of 1 means that the transition/co-occurrence will always occur, whereas a value of 0 means that the transition's likelihood is exactly what it would be if we were to predict the transition using only the base frequency of the destination state. Values above 0 signify that the transition is more likely than expected (i.e., greater than the base frequency of the destination behavior or affective state), and values under 0 signify that the transition is less likely than expected (i.e., less than the base frequency of the destination behavior or affective state).

For a given transition or co-occurrence, we calculate a value for ***L*** for each student and then calculate the mean and standard error across students. We can then determine if a given transition is significantly more likely than chance (chance=0) using the two-tailed t-test for one sample. Note that the degrees of freedom for a two-tailed t-test for any given transition or co-occurrence is the number of students for whom equation 1 can be calculated, minus one ($df = N - 1$). Students who never displayed the preceding affective state or behavior give no evidence on transitions from that affective state or behavior. Similarly, it is not possible to calculate transition likelihood for students who always displayed the same following affective state or behavior.

In analyzing the affective states that precede, follow, and co-occur with each of the student behaviors studied, it was not possible to study gaming the system due to its low frequency. On-task solitary behavior was not explicitly studied, as it was the baseline behavior of use for these systems. Hence, we studied the relationship between off-task behavior and on-task collaboration, and the four affective states studied.

The full pattern of transitions and co-occurrence between affect and student behavior is shown in Table 3.

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-occurence (denoted by dash-dash) within the data set. Statistically significant transitions ($p<0.05$) in boldface; marginally significant transitions ($p<0.1$) in italics.

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)

The pattern between boredom and off-task behavior was somewhat non-intuitive. First, boredom and off-task behavior co-occurred, $t(26) = 2.58$, two-tailed p =0.02. However, a student who was bored was not more likely to go off-task in the next observation, $t(11) = -0.63$, two-tailed p =0.54. But surprisingly, a student who was off-task was significantly *less* likely to be bored in the next observation, $t(23)= -3.05$, p = 0.01. This finding suggests that off-task behavior relieves boredom, in turn suggesting that off-task behavior may disrupt the "vicious cycles" of continual boredom that have been reported in [1, 6].

The dynamics between frustration and off-task behavior was also interesting. A student who was frustrated was marginally less likely to go off-task in the next observation, $t(11) = -2.03$, two-tailed p =0.07. Off-task behavior and frustration also were less likely than chance to co-occur, $t(26) = -2.06$, two-tailed p =0.05. There was not a statistically significant relationship between off-task behavior and future frustration, $t(23) = 1.51$, two-tailed p =0.15.

No other affective states were significantly more or less likely than chance to precede or follow off-task behavior. However, both engaged concentration and confusion were significantly less likely when a student was off-task, respectively, $t(26) = -5.35$, two-tailed $p <0.001$, $t(26) = -3.49$, two-tailed $p <0.01$.

On-task conversation was not significantly preceded by any affective states. However, it was significantly less likely than chance to precede frustration, $t(42) = -2.11$, two-tailed p =0.04. Hence, it appears that on-task conversation resolves problems that might cause future frustration.

In terms of co-occurrence, students were significantly more likely than chance to be confused while engaging in on-task conversation, $t(43) = 3.92$, two-tailed $p < 0.001$. We hypothesize that a confused student might seek help, increasing the likelihood of being on-task. Students were significantly less likely than chance to be bored while in on-task conversation, $t(43) = -2.92$, 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, a particularly striking finding given the higher probability of engaged concentration following 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.

4 Discussion and Conclusions

Within this paper, we have analyzed the affect which precedes, co-occurs with, and follows two forms of behavior that occur outside of interactive learning environments: off-task behavior, and on-task conversation. This analysis was carried out on field observation data from undergraduates using virtual laboratory software for chemistry.

Perhaps the most noteworthy finding is that off-task behavior co-occurs with boredom, but that boredom is significantly less likely than chance following off-task behavior. The complex relationship between 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 [e.g. 12]. Overall prevalence may simply not be a sufficiently sensitive measure to catch the relationships between off-task behavior and affect.

Past theories of off-task behavior have frequently focused on its negative correlates, such as poorer learning [e.g. 3, 8, 11, 13], and skipping school and drop-out [e.g. 7, 23]. However, our findings suggest that off-task behavior may play a positive role in some situations, disrupting "vicious cycles," where a student who becomes bored is highly likely to remain bored [e.g. 1, 6], and helping some students regulate their boredom. A similar finding is obtained in [20], where frustrated students who go off-task were seen to demonstrate future engagement. Hence, off-task behavior, within reasonable limits, may actually be beneficial for affect and in turn perhaps even for learning. This finding accords with work by Kreijns [10] suggesting another positive effect of off-task behavior, improved relationships between students (and in turn improved collaboration).

We also find interesting relationships between on-task conversation and affect. In specific, on-task conversation is associated with less future probability of frustration (even when students are working solitarily). Much research on collaborative and individual learning attempts to determine which form of learning is most effective, and under which conditions. However, this finding confirms earlier reports that episodes of on-task conversation are a normal part of "individual" learning in classrooms [e.g. 3, 22], and goes further, suggesting that collaborative episodes during individual learning often lead to the types of affect and concentration that are associated with successful learning. It may be interesting to investigate, in future research, what the affective impacts are of periods of individual work during collaborative learning.

Overall, the findings presented here suggest that the interplay between student behavior and affect, within educational settings, is more complex than previously thought. This result warrants further fine-grained analysis of the effects of off-task behavior during learning, and the factors leading to and effects of on-task collaboration. By understanding these relationships, we may be able to design learning environments that better leverage the positive aspects of off-task behavior and on-task conversation, while minimizing the negative impacts of off-task behavior on learning.

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