The Effects of Motivational Modeling on Affect in an Intelligent Tutoring System

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Keywords: Motivation, affective transitions, intelligent tutoring systems, pedagogical agents

Abstract: A motivationally-aware version of the Ecolab system was developed with the aim of improving the learners' motivation. To gain some insight into the effects of motivational modeling on students' affective states, we observed the affect of 180 students interacting with either Ecolab or M-Ecolab. The affective states considered were based on existing coding schemes [10]. The results suggest that the motivationally-aware tutoring system seems to maintain students' delight over time. However, it seems the motivational interventions did not create new "virtuous cycles" of positive affect [10], or disrupt "vicious cycles", where a student persists in a negative affective state.

Introduction

Affective computing refers to "computing that relates to, arises from, or deliberately influences emotions" [20]. It is founded in part on the recognition that human intellectual life is influenced and regulated by non-cognitive inputs such as emotions and motivation. In recent years, researchers have become particularly interested in how affect influences student learning and experiences within educational software such as intelligent tutoring systems, and have begun to work towards the design and development of affective learning companions for use within those systems (cf. [8]). To keep a learner focused on a task, an *affective learning companion* should be able to detect learner emotions and respond with appropriate levels of support [1, 5, 7, 20, 21].

To inform the design of affective learning companions, researchers are increasingly investigating affective dynamics, or natural shifts in learners' affect over time, and how these influence learner behavior towards designing learning interactions which influence student affect in a smooth and natural fashion (cf. [3, 10]). These studies attempt to determine which affective states tend to persist; which transitions, given a state, are most likely to occur; and which states tend to lead to a learning or non-learning behavior. The combination of these analyses has led to the discovery of “virtuous cycles” where learning-positive behaviors (such as flow – [9]) persist, and “vicious cycles” where learning-negative behaviors such as frustration and boredom persist ([10, 3]). There is also evidence suggesting that boredom and confusion lead to behaviors associated with poor learning [23] such as gaming the system (“attempting to succeed in an interactive learning environment by exploiting properties of the system rather than by learning the material” – cf. [2]). On the other hand, confusion can prevent learners from transitioning into boredom, and has been associated with positive learning in some studies [10].

In this paper, we study the differences in learners’ affective dynamics in two learning environments on ecology for young learners: Ecolab [16] and M-Ecolab [22]. In terms of cognitive content and pedagogy, the two environments are exactly the same. The principal difference is that M-Ecolab incorporates motivational scaffolding whose behavior is driven by a model of the learner’s motivation, while Ecolab does not. The motivational scaffolding in Ecolab provided a context to study the effects of “motivationally aware” tutoring systems and the reciprocal influence between the system and the learner [21]. In this context motivation was understood as the learners’ willingness to exert more effort and their desire to seek more challenging activities while being more independent from the on-line help [22]. Previous M-Ecolab studies provided an insight into the effects of motivational scaffolding in the learners’ motivation and learning [21] but did not consider the learners’ affective states such as frustration, boredom or flow and their interaction with motivation although a positive influence was expected. This paper focuses on determining how the presence of motivational scaffolding influences a learner’s affective state and understanding the affect in Ecolab and M-Ecolab, in the context of previous research on affect in interactive learning environments (cf. [3, 10]). Can a motivational agent encourage positive affective states, such as flow and delight? Can the agent help sustain virtuous cycles? And, correspondingly, can a motivational agent help students avoid negative affective states or disrupt vicious cycles?

1. Ecolab and M-Ecolab

Ecolab was developed to gain a better understanding of how to design a computerised more-capable partner that offers adaptive scaffolding in Ecology [16]. M-Ecolab follows the same philosophy and domain and extends Ecolab to incorporate motivationally adaptive scaffolding [22]. Ecolab and M-Ecolab assist primary school children in the process of learning feeding relationships between different species of organism. They are based on the metaphor of an ecology laboratory and enable learners to add plants and animals to a virtual environment as well as to view that environment from different perspectives such as an energy view or a web diagram. Learning activities in Ecolab consist of a network of ten learning nodes where help specific to every learning node is provided with four levels of help messages. Help at the motivational level is given in M-Ecolab via an affective learning companion whose demeanor changes considering the learner’s degree of motivation as assessed with a motivational model [22]. The motivational model of each student keeps track of data such as help provided, correct or incorrect actions associated to individual nodes, the learner’s persistence, etc. The model is used to determine whether motivating feedback should be presented, which type of motivational feedback to present (to sustain or improve motivation) and the demeanor used by the companion to deliver it (alterations of the agent’s facial expression and tone of voice). In M-Ecolab the motivating reactions were framed in a narrative where the affective companion plays the role of another child who has worked with the M-Ecolab before and is there to help other children. The affective companion helps students solve the learning activities for which the learner’s motivation is low. Every successfully completed activity provides a letter to form a password which, when completed, opens up a treasure chest [21]. Updating the motivational model each time a new learning activity is selected allows dynamic activation or deactivation of the motivating techniques. For example, if a low state of motivation is detected, the affective companion would use a worried facial expression (motivation enhancing strategy on right, Figure 1) and the spoken feedback would say: "You're doing well but now try to do even more actions within the activity and if you make an error try again to do the correct action!" A more detailed description of M-Ecolab's motivational support is provided in [21].

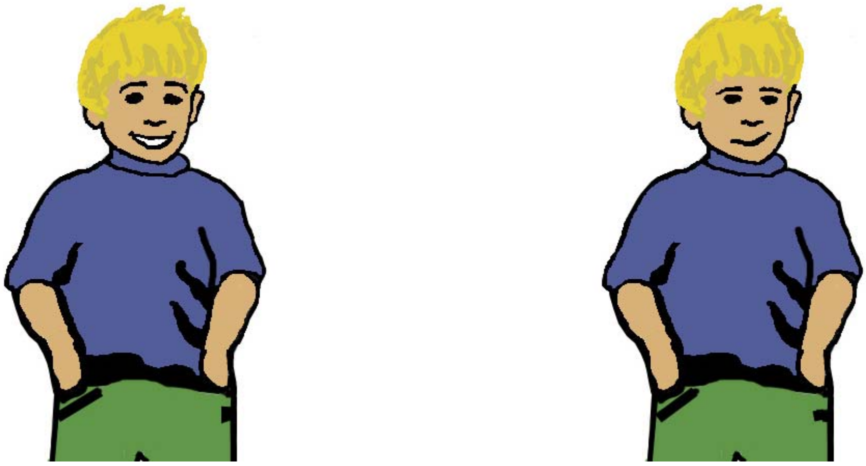

Figure 1. Happy (left) and neutral (right) facial expressions in the context of M-Ecolab

2. Participants and study methods

Affective states and transitions among students were studied in two private, co-educational grade schools in the Philippines. 80 students from an urban Quezon City school and 100 students from a provincial Cavite school participated in the study. Student ages ranged from 9 to 13, with the mean, median and mode ages of 11.5 years old.

Because of the limited number of computers and observers available for the study, the students were divided into groups of 10, one group per observation session. When each group entered the computer laboratory, each student was randomly assigned a computer. Computers 1 to 5 had Ecolab, while computers 6 to 10 five had M-Ecolab. Students were not told which version of the software they were using.

Each student used Ecolab or M-Ecolab for 40 minutes, and each student's affect was observed 12 times as he or she used the software. The observations of affect were conducted using Baker, Rodrigo, & Xolocotzin's [3] method for quantitative field observations of student behavior and affect. The observations were carried out by a team of three observers, working in pairs during any given observation session. One observer was taking her master's degree in education. The other was taking her MS in Computer Science. The third was a research assistant with an MS in Computer Science. All had prior teaching experience. Two of the observers had prior experience conducting these observations (cf. [3] and [24]) – the third observer was trained using the same protocol as those observers, prior to this study. As in [3], each observation lasted twenty seconds, and was conducted using peripheral vision, i.e. observers stood diagonally behind or in front of the student being observed and avoided looking at the student directly, in order to make it less clear exactly when an observation was occurring. Each group of observers was assigned to 10 students and alternated between them. Since each observation lasted twenty seconds, each student was observed once per 180 seconds.

Within an observation, each observer coded the student's affective state. The affective categories coded were boredom, confusion, delight, surprise, frustration, flow, and the neutral state, as in [3, 10]. Since many behaviors can correspond to an emotion, the observers looked for students' gestures, verbalizations, and other types of expressions rather than attempting to explicitly define each category, using a coding scheme developed in prior research [3]. It is possible for a student to exhibit more than one affective state during an observation period – for tractability, only the first affective state observed was coded. Interrater reliability was reasonably high. Cohen's [6] κ=0.73 for Ecolab observations and κ =0.71 for M-Ecolab observations.

The students also answered a learning test associated with Ecolab evaluations both before (pre-test) and after (post-test) using the software. However, because of problems in the administration of the pre-test, results regarding learning gains cannot be considered conclusive and are therefore not reported in this paper. Previous evaluations of Ecolab [16] and M-Ecolab [21], however, provide more information regarding the effects of the software on students' learning gains.

3. Analytical methods

The following sections consider both the overall prevalence of each affective state within Ecolab and M-Ecolab and the likelihood of transitions between states, specifically looking at how a student's current affective state influences the probability of a student being in the same specific affective state or a different state 180 seconds later. In computing the likelihood of an affective transition, it is important to take into account the base rates of each affective category . Flow was the most frequent affective state within both systems; hence, flow is likely to be the most common affective state that follows any other affective state. It is important for our metric to account for the temporal relationship between states, not just how common each state is overall. Hence, in order to appropriately account for the base rate of each affective category in assessing how likely a transition is, D'Mello's [10] transition likelihood metric, **L** was adopted. This metric is statistically equivalent to Cohen's κ [6]. D'Mello et al's **L** [10] gives the probability that a transition between two affective states will occur, given the base frequency of the destination state, and is computed:

$$L = \frac{\Pr(NEXT \mid PREV) - \Pr(NEXT)}{(1 - \Pr(Next))}$$

L is scaled between 1 and - ∞. A value of 1 means that the transition will always occur. A value of 0 means that the transition's likelihood is exactly what it would be given only the base frequency of the destination state (i.e. this transition occurs with exactly the frequency that would occur if transitions were random). Values above 0 signify that the transition is more likely than it could be expected to be given only the base frequency of the destination state, and values under 0 signify that the transition is less likely than it could be expected to be, given only the base frequency of the destination state.

For a given transition, **L** was calculated for each student and then the mean and standard error across students were obtained. Given these results, it is possible to determine if a given transition is significantly more likely than chance, given the base frequency of the next state, using the two-tailed t-test for one sample. This paper only reports a small subset of the possible tests that could be reported; however, the overall pattern of significant transitions is for each system very unlikely to be due to chance ($p<0.001$ in Ecolab, $p=0.03$ in M-Ecolab, computed using a 100,000 run Monte Carlo simulation [cf. 19]).

4. Results

In understanding how the motivational features of M-Ecolab impact student affect, we compare the affect and affective state transitions between the two systems.

4.1 Affect frequency in Ecolab and M-Ecolab

As shown in Table 1, the most common affective state in Ecolab (61.5%) and M-Ecolab (67.4%) is Flow. This is in the same range as other learning systems studied using this method and similar populations, including Aplusix (68%) [24] and The Incredible Machine (62%) [23]. In Ecolab and M-Ecolab, flow is more common than reported for AutoTutor (20%) [10], a conceptual dialog learning system, although this difference is likely due to differences in method and population, as that study was conducted in a lab setting in the United States.

Table 1. Frequency of each affective state in Ecolab and M-Ecolab. Standard deviations given in parentheses

Affective State	Ecolab	M-Ecolab
Boredom	15.2% (18.5)	12.0% (16.7)
Confusion	12.7% (10.8)	12.9% (12.1)
Delight	3.3% (6.9)	3.7% (6.7)
Flow	61.5% (21.5)	67.4% (20.5)
Frustration	5.8% (10.7)	3.3% (8.0)
Neutral	1.0% (3.0)	0.6% (2.2)
Surprise	0.3% (1.6)	0.01% (1.1)

However, Boredom is also common in Ecolab (15.2%) and M-Ecolab (12%); Boredom in these systems is roughly comparable to AutoTutor (16%) [10], but more common than in The Incredible Machine (7%) or Aplusix (3%). As boredom is associated with inappropriate use of educational software [23] and significantly poorer learning [8], there is evidence that there remains considerable room for improvement in students' affect as they use Ecolab. Frustration was rare in Ecolab (5.8%) and M-Ecolab (3.3%), rarer than in previous results involving AutoTutor (11%) but close to previous results in The Incredible Machine (6%) and Aplusix (2%). Delight was fairly uncommon in Ecolab (3.3%) and M-Ecolab (3.7%) in line with previous results involving AutoTutor (3%) and possibly lower than in The Incredible Machine (6% -- [23]).

These results suggest that both Ecolab and M-Ecolab are generally successful in encouraging Flow and avoiding Frustration but that students still experienced a considerable amount of Boredom. If M-Ecolab encourages better affect as compared to Ecolab, we could expect a lower frequency of negative affect states (Boredom and Frustration) and perhaps also a higher frequency of positive affect states (Flow and Delight). To investigate this, between-subjects analyses of the differences between the percentages observed were carried on. The difference between Boredom (Ecolab = 15.2%, M-Ecolab = 12%) was not statistically significant ($t(178)=1.21$, $p=0.22$, two-tailed t-test assuming equal variances); there were also not statistically significant differences between environments in the occurrences of frustration ($t(178)=1.78$, $p=0.07$), flow ($t(178)=-1.86$, $p=0.06$), or delight ($t(178)= -0.27$, $p=0.78$).

4.3 Affect transitions in Ecolab and M-Ecolab

Another key aspect of a system's effects on affect is the dynamics of affective transitions within that environment.

Ecolab does not seem to be able to disrupt the types of negative affect studied. A student who is bored within Ecolab is significantly more likely than chance to still be bored 180 seconds later (***L***=0.28, t(59)=4.64, two-tailed p<0.01) and is unlikely to transition into flow (***L***= -0.76, t(59)=-5.59, two-tailed p<0.01), as shown in Table 2. A student who is frustrated within Ecolab is also more likely than chance to still be frustrated 180 seconds later (***L***= 0.21, t(32)=3.43, two-tailed p<0.01). Still, Ecolab is seen to support flow, a positive result. A student who is in flow is likely to stay in flow (***L***=0.19, t(90)=2.98, p<0.01). Students in flow are also particularly unlikely to transition into boredom (***L***=-0.06, t(90)=-3.93, p<0.01). Surprise was the rarest affective state observed. Students observed to be in delight, flow, frustration, neutral or surprise are less likely to transition to surprise. This supports the hypothesis [cf.3] that surprise may be conceptualized as a transitive affective state, as opposed to a more durable affective state such as boredom, confusion, flow, and frustration. A full table of affect transitions within Ecolab is given in Table 2.

Table 2. The transitions between affective states in Ecolab. Horizontal rows represent previous affective states, and vertical columns represent affective states one minute later. The first number in each cell is the mean value of D'Mello's *L* across students, the number in parantheses is the standard deviation. Cells with insufficient sample size to compute *L* are left blank (but can be inferred to be quite rare). Statistically significant relationships are in dark grey. Marginally significant relationships are in light grey.

	BOR	CON	DEL	FLO	FRU	NEU	SUR
BOR	0.283 (0.47)	-0.004 (0.34)	-0.005 (0.11)	-0.755 (1.04)	0.056 (0.29)	0.001 (0.07)	0.005 (0.07)
CON	-0.048 (0.31)	-0.018 (0.20)	0.007 (0.19)	0.176 (0.88)	-0.008 (0.17)		0.001 (0.04)
DEL	-0.081 (0.31)	0.110 (0.48)	0.041 (0.15)	-0.286 (1.19)	0.014 (0.28)	0.033 (0.14)	-0.004 (0.00)
FLO	-0.062 (0.15)	-0.004 (0.19)	-0.001 (0.08)	0.188 (0.60)	-0.007 (0.11)	-0.006 (0.02)	-0.002 (0.01)
FRU	0.158 (0.45)	0.010 (0.31)	-0.027 (0.04)	-0.771 (1.00)	0.206 (0.34)	-0.010 (0.00)	-0.004 (0.00)
NEU	0.039 (0.40)	-0.145 (0.00)	0.118 (0..35)	0.037 (1.26)	-0.061 (0.00)	0.027 (0.11)	-0.004 (0.00)
SUR	0.056 (0.53)		0.172 (0.46)	-0.040 (0.00)	-0.016 (0.00)		-0.004 (0.00)

The persistence of boredom and frustration in Ecolab does not seem to have been altered by M-Ecolab. A full table of affect transitions within M-Ecolab is given in Table 3.

Table 3. The transitions between affective states in M-Ecolab. Horizontal rows represent previous affective states, and vertical columns represent affective states one minute later. The first number in each cell is the mean value of D'Mello's *L* across students, the number in parantheses is the standard deviation. Cells with insufficient sample size are left blank (but can be inferred to be quite rare). Statistically significant relationships are in dark grey. Marginally significant relationships are in light grey.

	BOR	CON	DEL	FLO	FRU	NEU	SUR
BOR	0.267 (0.41)	-0.068 (0.18)	0.010 (0.18)	-0.530 (1.31)	-0.013 (0.09)	-0.006 (0.00)	-0.002 (0.00)
CON	-0.032 (0.26)	0.013 (0.24	0.008 (0.16)	-0.132 (1.09)	0.047 (0.24)	0.008 (0.07)	-0.002 (0.00)
DEL	-0.126 (0.05)	-0.082 (0.23)	0.120 (0.31)	0.162 (1.23)	0.013 (0.20)	-0.006 (0.00)	0.007 (0.05)
FLO	-0.017 (0.18)	-0.001 (0.18)	-0.009 (0.06)	0.109 (0.64)	-0.007 (0.09)	-0.004 (0.01)	0.0001 (0.01)
FRU	0.056 (0.40)	-0.030 (0.31)	0.100 (0.37)	-0.826 (1.40)	0.148 (0.32)	0.009 (0.06)	-0.002 (0.00)
NEU	-0.137 (0.00)	-0.148 (0.00)	0.092 (0.37)	0.362 (1.21)	0.009 (0.12)	0.036 (0.12)	-0.002 (0.00)
SUR	-0.137 (0.00)	-0.148 (0.00)	0.038 (0.00)	-0.021 (1.77)	0.311 (0.60)	-0.006 (0.00)	-0.002 (0.00)

A student who is bored in M-Ecolab is likely to still be bored (L=0.28, t(53)=4.92, two-tailed p<0.01) 180 seconds later, and a student who is frustrated is likely to still be frustrated 180 seconds later(L=0.15, t(23)=2.18, two-tailed p=0.04). The ***L*** values for persistence of boredom, t(132)=-1.48, p=0.14, and frustration, t(40)=0.54, p=0.58, were not significantly different between systems, using two-tailed t-tests assuming equal variances.

In M-Ecolab, there is a statistically significant likelihood that a student seen in delight continues in delight in 180 seconds later (***L***=0.12, t(30)=2.13, two-tailed p=0.04). In Ecolab, this did not appear to be the case (***L***=0.04, t(53)=1.08, p=0.28). The difference in the prevalence of delight between systems, though, was not statistically significant (t(53)=-1.21, two-tailed p=0.22). Students using M-Ecolab who were in delight were not likely to transition into boredom (***L***=-0.13, t(30)=-12.92, two-tailed p<0.01) or into confusion (***L***=-0.08, t(30)=-1.92, two-tailed p=0.07). However, the persistence of flow was not quite statistically significant in M-Ecolab (***L***=0.11, t(90)=1.61, two-tailed p=0.11). However, the difference between Ecolab and M-Ecolab was not significant (t(178)=0.85, p=0.39).

5. Discussion and conclusions

From the analyses, neither Ecolab nor M-Ecolab seem to be able to disrupt the persistence of boredom and frustration in students over time. However, it appears that both environments are able to sustain some positive affective dynamics; flow is persistent in Ecolab (significant) and M-Ecolab (approaches significance). Additionally, delight is persistent in M-Ecolab, and is not persistent in Ecolab. It is not yet clear what factors explain the persistence of delight in M-Ecolab, whether it is the motivational strategies, the narrative, other incentive to open the treasure chest. It will be valuable to analyze in future research, which aspect of M-Ecolab led to the persistence of delight. However, none of these factors appear to have been successful at either reducing or disrupting boredom and frustration. Boredom is of particular concern as it has been show to persist in multiple prior learning systems [4] and has been associated with behaviors such as gaming the system which reduce learning [23]. Further research into boredom and ways in which boredom might be disrupted may be valuable to the field. Some possible ways of addressing boredom include the motivation enhancing techniques cited in [12, 13, 17]. The work of Klein et. al. [14] on how to alleviate frustration may also be relevant for future improvements of M-Ecolab.

The main contribution of this paper is that the motivational interventions used in M-Ecolab did not appear to impact boredom, but did lead to delight persisting over time. However, in both Ecolab and M-Ecolab, boredom and frustration were persistent. Because of this, it will be important in future work to enhance the motivational model to detect frustration (cf. [11, 18]) and boredom and provide motivating scaffolding when theseaffective states aredetected.

Acknowledgements

We thank the administrators, faculty, and students of St. Alphonsus Ligouri Integrated School and Kostka School of Quezon City, and Dr. Celeste T. Gonzalez for their assistance in organizing and conducting the studies reported here. The work presented in this paper was funded in part by a research grant from the Ateneo de Manila University, Mexico's Council for Science and Technology (CONACYT) and by NSF award SBE-0354420 to the Pittsburgh Science of Learning Center: Studying Robust Learning with Learning Experiments in Real Classrooms.

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