Exploring the impact of a learning dashboard on student affect

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Abstract. Research highlights that many students experience negative emotions during learning activities, and these can have a detrimental impact on behaviors and outcomes. Here, we investigate the impact of a particular kind of affective intervention, namely a learning dashboard, on two deactivating emotions: boredom and lack of excitement. The data comes from a study we conducted with over 200 middle school students interacting with an intelligent tutor that provided varying levels of support to encourage dashboard use. We analyze the data using a range of techniques to show that the learning dashboard is associated with reduced deactivating emotions, but that its utility also depends on the way its use is promoted and on students' gender.

Keywords: affect, learning dashboard, intelligent tutoring system.

1 Introduction

A key factor that influences students' academic success is their emotions and affective experiences while learning. For instance, positive affect has a facilitative effect on cognitive functioning in general [11], and on creative problem solving in particular [12, 15]. Even emotions traditionally viewed as negative can be beneficial, e.g., confusion is associated with learning under certain conditions [10]. In contrast, the affective state of boredom reduces task performance [16] and increases ineffective behaviors like gaming [7]. Given the pivotal role that affect plays, there is growing interest in developing educational technologies that recognize and respond to student affect. To date, however, the emphasis has been on the former, namely affect recognition through the construction of user models [8, 20]. Thus, little work exists exploring the impact of affective support.

Our research takes a step in this direction by analyzing the impact on affect of a particular kind of intervention, namely a *learning dashboard*. The dashboard graphically and textually presents individualized reports about student progress and performance, e.g., problems solved, utility of strategies used, knowledge gained (shown in Figure 1 and described in Section 2.1). Prior work has utilizing learning dashboards for supporting cognitive or meta-cognitive behaviors. For instance, Arroyo et al. [3]

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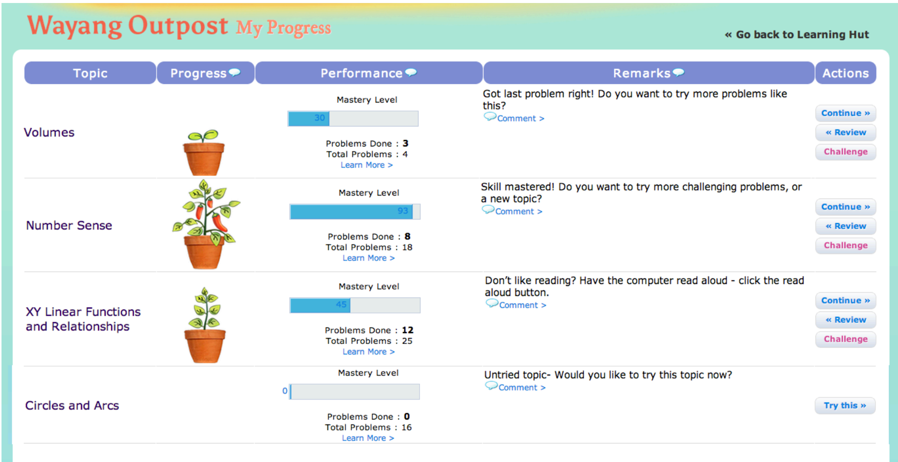

Fig. 1. The Student Progress Page (SPP) encourages students to reflect on their effort (plants, column 2) for each math topic, reflect about their mastery (bars, column 2) and recent behaviors (column 4), and make informed decisions about challenging themselves with harder problems (column 5).

integrated a basic progress chart into an intelligent tutor and found that students who had access to the chart had higher learning gains. On the meta-cognitive side, learning dashboards reifying student gaming behaviors (e.g., hint abuse) have been shown to discourage gaming [6, 19]. Since a learning dashboard shows students the system's assessment of their skills or behaviors, it is a step towards *open learning models* (OLM) that can be viewed or accessed by learners [9]. Several studies have shown that OLM improved learning [13] and self reflection [18].

In contrast to the above-described research focusing on cognitive or meta-cognitive outcomes, a recent study analyzed the impact on affect of an affective agent Scooter, which appears angry when students game [14]. While overall, no effect was found on students' affect, Scooter's responses were limited to affective expressions, which may be insufficient to influence student affect.

Following Zimmerman & Moylan's [21] model of self-regulation, we hypothesize that a learning dashboard has the potential to reduce negative affect, since it can help students self regulate, e.g., feel less "lost" in the learning process, set goals, and reflect on progress towards those goals. Here, we focus on *deactivating negative* emotions, including boredom and lack of excitement, because these can be especially detrimental to student learning [7]. Our target domain is mathematics during middle school, a very challenging

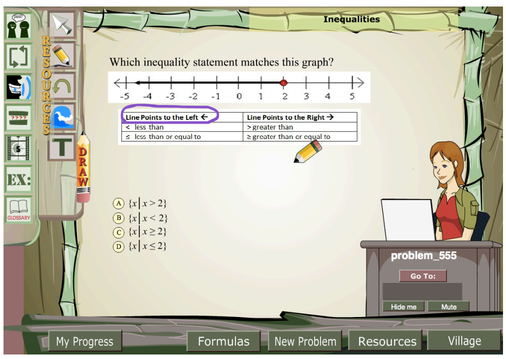

Fig 2. MathSpring. A button (bottom left) allows students to access the Student Progress Page (SPP).

topic for many students. By the time students reach high school, they report boredom and lack of excitement in mathematics at an alarming rate [2]. Thus, there is a real need to address these emotions earlier, e.g., during middle school.

2 The Tutor and Student Progress Page (SPP)

This research was conducted within an established intelligent mathematics tutor called MathSpring (formerly called Wayang) (see Figure 2) [1]. The tutor includes a student model that assesses individual students' knowledge and effort exerted and adapts the choice of problem accordingly [4]; it also provides hints and explanations and worked-out examples. To expand the range of support offered, we have integrated into MathSpring a learning dashboard we call the *student progress page* (SPP).

As shown in Figure 1, the SPP lists the available domain topics as rows. Students click on a topic to view a list of problems available, along with details about their progress in that topic to encourage reflection about that topic, as follows:

- **Progress (Column 2).** The tutor shows its assessment of the student's problem-solving effort for problems in a given topic. The tutor makes this inference based on student behavior (e.g., help seeking behavior, incorrect answers, time spent reading problems and hints, quick guesses). To visualize progress, the tutor uses the metaphor of a potted plant that grows if students invest effort, bares fruit when the topic is mastered, or withers when the system detects lack of student effort.
- **Mastery (Column 3):** This is a probabilistic assessment of student knowledge for each topic (column 1) based on Bayesian knowledge tracing.
- **Feedback (Column 4):** The tutor provides customized feedback based on the student's overall performance and most recent behavior, e.g., "*That last problem was a hard one. Good work!*"; "*You got the last problem right! Do you want to try more problems like this?*". The tutor also highlights instances when student behaviors are sub-optimal, e.g., "*You don't seem to have spent time reading the problems –did you know there is a 'read aloud' button?"*
- **Navigation (Column 5):** Students can choose different modes of navigation for subsequent problems (e.g., review prior problems, work on higher difficulty 'challenge' problems); tutor recommendations are provided (e.g., "*You have already mastered this topic. Maybe you should try 'challenge' problems or a new topic*.")

3 Experiment and Results

To evaluate the impact of the Student Progress Page on student affect, we conducted a study with grade seven students ($N = 209$). Students used MathSpring over three consecutive class sessions. On part of the first and last day, students filled in an pre- and post-affect survey, respectively, which included questions related to various types of affect, including interest and excitement, and so provided baseline data on affect.

To obtain information on affect, MathSpring prompted students to self-report their affect every five minutes, or every eight problems, whichever came first, but only after a problem was completed to avoid interruption. The prompts were shown on a separate screen and asked students to report on a target emotion (interest or excitement) via a 1-5 point Likert scale (e.g., for interest, "*How interested are you feeling right now? Not at all interested* (1) *… somewhat interested (3) … extremely interested* (5)*;* an analogous question appeared for excitement and the software cycled through the two emotions and students typically self reported several times on each emotion).

The study used a between subjects design with four conditions that ranged in terms of degree of access to the SPP tool: (1) *no-button* (N = 49): the SPP button was not present in the MathSpring interface (the only way to access SPP was through a convoluted set of steps that students were not informed about), (2) *button* (N = 53)*:* the SPP button was present and prominent but MathSpring did not encourage SPP use, (3) *prompt (N* = 52)*:* MathSpring invited students to view the SPP immediately after they self-reported low interest or low excitement (< 3), but students could ignore this invitation, (4) *force (N* = 55*)*: same as in *prompt* except that MathSpring took students to the SPP page and viewing it was not optional. Students within a given class were randomly assigned to one of the four conditions.

Prior to data analysis, as manipulation check we verified that SPP access indeed increased across conditions, from *no-button* to *force*: M = 1.3, M = 3.1*,* M = 6.0, M = 8.8. We also confirmed that there were no differences between conditions in terms of baseline interest and excitement as measured by the pre-affect survey (*ns*).

3.1 Does the Student Progress Page impact student affect?

To determine the impact of SPP on affect, we obtained a mean value of self-reported *interest* and *excitement* for each student using the student's self-report data. For excitement, the *no-button* and *force* conditions had the lowest (M = 2.5) and highest reported excitement (M = 2.8), respectively, with little difference between the middle two conditions (M = 2.6 for both). For interest, the *force* condition had the lowest value (M = 2.5), and there was little difference between the other three conditions (M = 2.7 for all three). Neither affective state produced a significant overall effect or significant follow-up pairwise comparisons as reported by an ANCOVA with the target emotion as the independent variable, the corresponding pre-affect survey emotion as the covariate baseline, and condition as the independent variable (*ns*).

In our prior work, we found that gender was an important factor in terms of students' reception of affective support [5]. Thus, we conducted follow up exploratory analyses splitting across gender. Fig. 3 shows the mean affect for each gender and condition. We first checked that baseline affect (obtained from pre-affect survey data for each target emotion within a given gender) was not different across conditions; two marginal baseline differences between conditions emerged for male students for excitement, despite the random assignment: *prompt* vs. (1) *force* (p = *.07*) and *(2) button* (p = *.1*). Thus, to avoid confounding our results, these two comparisons were excluded from further consideration. We then carried an ANCOVA as for the overall analysis that collapsed across gender (see above) but within each gender.

For excitement, female students reported similar levels of excitement for the top three SPP-access (*button, prompt, force*) conditions, and no effects were significant. In contrast, male students reported marginally higher excitement in the *force* condi-

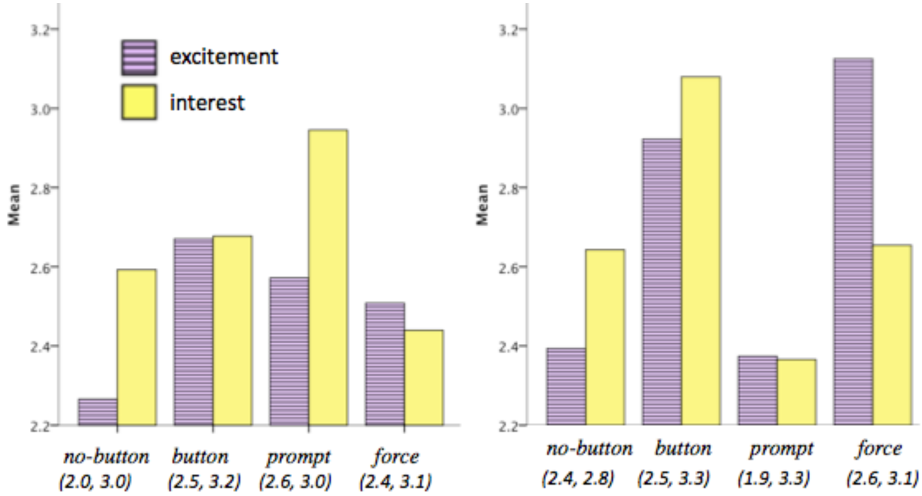

Fig. 3: Mean excitement and interest for female students (left) and male students (right); the bottom row shows the baseline affect (*excitement*, *interest*) from the pre-affect survey.

tion than the *no-button* condition (p = .08). This suggests having the tutor force SPP usage may have increased overall self-reported excitement for male students.

For interest, female students reported marginally lower interest in the *force* condition than in the *prompt* condition (p = .1). Male students, on the other hand, reported lower interest in the *prompt* condition than *button* condition (p = .1). To further explore this effect of prompting vs. forcing SPP usage between the male and female students, we conducted exploratory analysis by restricting the analysis to the *prompt* and *force* conditions. We first checked that there were no baseline differences between genders in interest and this was the case (*ns*). An ANCOVA with *gender* and *condition (prompt* vs. *force)* as the independent variables, *interest* as the dependent variable, and baseline *interest* as the covariate revealed a marginally significant interaction between gender and condition (p = .9). This interaction (See Fig. 3) indicates that female students reported higher interest when MathSpring prompts gave them the choice to use SPP rather than when it enforced SPP usage, while the opposite pattern existed for male students.

3.2 Is Student Progress Page usage associated with positive affect?

Another way to analyze the impact of SPP is to check for associations between its usage and affect, and in particular to evaluate if higher SPP usage is associated with less deactivating emotions (boredom, lack of excitement). However, this analysis is complicated by the fact that MathSpring encouraged SPP usage in two of the conditions (*prompt* and *force*) when low interest or low excitement was self reported. Thus, SPP usage could be correlated with *negative* emotions in these two groups. In contrast, in the other two conditions (*no-button* and *button*), students were not encouraged to view the SPP and so it was up to them to access the tool or not. To take these considerations into account, we checked for correlations between SPP usage and self-reported affect separately in each of these two groups.

For the *SPP not promoted* group *(no-button, button* conditions*),* interest was positively associated with SPP usage (r = .24, p = .023) – excitement also was positively associated with SPP but this did not reach significance (r = .13, p = .26). One explanation for these findings is that in the *SPP not promoted* conditions, students who had positive affect to begin with (high interest and excitement) used SPP more because they were more motivated, and so SPP usage did not impact affect per se. To check for this possibility we controlled for students' pre-existing affect as derived from the pre-affect survey by running partial correlations. We found that the results held, i.e., interest was still significantly associated with SPP usage (r_p= .25, p = .036) and the result for excitement did not change (r_p = .14, p = .3). Overall, these results suggest that SPP usage may have improved student affect, but given the correlational nature of this analysis these results should be interpreted with caution.

In contrast, for the *SPP promoted (prompt, force* conditions*),* as predicted interest was negatively associated with SPP usage (r = -.32, p < .01); there was also a trend for excitement being negatively associated with SPP but this did not reach significance (r = -.15, p = .16). These results held after controlling for the pre-affective survey data (r = -.31, p = .012 for interest; excitement-SPP correlation negative and *ns*).

3.3 How do conditions impact affective state transitions?

While the above analysis uncovered interesting indications of SPP impact, it did not shed light on how students transitioned between affective states (e.g., if they got "stuck" in the negative deactivating states in some conditions). Addressing this question requires information on student affect more frequently than provided by the self-reports. Thus, we generated affect predictions using two user models built from the data, one for each target emotion. Note that we did not use the models during the study to obtain affective information because that would have required having the data from this target population prior to the study, in order to construct the models (or alternatively having a model that was proven to generalize to the present population, which we did not have).

Affect Models. The affect models generate a prediction of a given student's target affect (interest or excitement) after each problem the student solves. While the two models were created specifically for this analysis, the methodology for their construction comes from our prior work – see [20]. Here, the models were trained using 4-fold student level batch cross validation over the target data set. Each model employed a total of 10 features to predict students' self reports. The excitement model used 2 features based on student's interactions with MathSpring; the interest model used 3. The models' performance (excitement R = 0.43, *Kappa* = 0.18; interest R = 0.46, *Kappa* = 0.28) are comparable with existing sensor free affect detector results [8].

High-level and Specific Path Models. Using the affect model predictions, we followed the procedure in [3] and generated Markov Chain models for the two target emotions for each condition. These high level "path" models provide the probabilities of transitioning between levels of a given affective state (e.g., from neutral to excited)

	No-button			*button*			*prompt*			*force*		
	N_E/N_I	E / I	¬E/B	N_E/N_I	E / I	¬E/B	N_E/N_I	E / I	¬E/B	N_E/N_I	E/I	¬E/B
N_E/N_I	.91/.71	0/.06	.09/.24	.76/.74	.21/.14	.03/.12	.73/.7	.17/.11	.09/.19	.72/.62	.23/.18	.04/.2
E/I	0 /.4	1 / .6	0 / 0	.11/.28	.89/.72	0 / 0	.03/.28	.96/.72	.01/ 0	.08/.48	.91/.52	.01/ 0
¬E/B	.41/.26	0 / 0	.59/.74	.33/.38	0/ 0	.67 /.62	.28/.2	0 / 0	.72/ .8	.39/.24	0/ 0	.61/.76

Fig 4. Visual representation of the high-level path models for excitement in the *no-button*, *prompt* and *force* conditions from left to right, respectively (top) and transition probabilities for all the high level path models (for each condition and target emotion), shown in text form (bottom): N_E = Neutral given that the target emotion is excited; N_I = neutral given that the target emotion is interested; E = excited; I = interested; ¬E = unexcited; B = bored

–we restricted this analysis to three levels for a given affective states (e.g., interest: *bored*, *neutral*, *interested*). Since the affect model outputs decimal values, we collapsed these so that values < 2.49 correspond to a negative affective state (*bored, unexcited*), values between [2.5 and 3.49] indicate the *neutral* state and values > 3.5 correspond to a positive affective state (*interested, excited*). We then calculated the transition probabilities (e.g., the probability of a transition from bored (B) to interested (I) = (#transitions B➔I) / [(#transitions B➔I) + (#transitions B➔B) + (#transitions B➔Neutral)]. The transition probabilities and models are shown in Fig. 4.

The path models provide a high level view of how a student transitions between levels of an affective state. For instance, we can ascertain that for excitement, overall the probability of transitioning from neutral to excited is the highest in the *force* condition (Fig. 4). However, these models are difficult to interpret and compare between conditions. This can be addressed by computing the joint probability of a student's affect undergoing particular transitions (i.e., following an *affective path*). For instance, given the condition forcing SPP usage, what is the probability that a student starting in a neutral state ends up excited? The next analysis answers such questions.

Assuming that a student starts in a "neutral state" with a certain prior probability, we can estimate the joint posterior probability of a given affective path. To illustrate, starting in a neutral state at time t_0, there are two alternative paths that take the student to an excited state: (P1) N→E→E, or (P2) N→ N→ E. The probability of path P1 is $P(S_{t2}=E \mid N\rightarrow E\rightarrow E) = P(S_{t0}=N) * P(N\rightarrow E) * P(E\rightarrow E)$, where $P(S_{t0}=N)$ is the prior probability of the student being in a neutral state at time 0 (obtained from affective pre-survey baselines). In general:

$$P(S_{t2} = S2 \mid S0 \rightarrow S1 \rightarrow S2) = P(S_{t0}=S0) * P(S0 \rightarrow S1) * P(S1 \rightarrow S2) \qquad [\text{ Eq 1. }]$$

The joint probability provides the probability of a given affective state after a specific path in the affect transition model. The individual transition probabilities (right-most two in Eq. 1) come from the high-level path models (Fig. 4). Here, we focus on paths of length two, and assume the starting point is the neutral state, but this analysis can be extended to any starting point and path length. To illustrate, Table 1 shows partial computations of the joint probability of a student following a certain affective path using Eq 1. In the case of the *no-button* condition, where there was very restricted access to the SPP, students were more likely to end up in unexcited state than excited at time t_2. Note these probabilities are very low (as the most likely affective state in paths of length 2 is "neutral", $P(St_2{=}N \mid St_0{=}N) \sim 0.3$ across conditions, which is reasonable as affect may not change drastically in short affective paths.

Table 2 aggregates and synthesizes the results of Table 1 for comparison across conditions. For excitement, Table 2 shows that the *no-button* condition fared worst compared to all other conditions. This suggests that in general, having the SPP present resulted in positive affective paths (ones that led to excitement). For interest, again the *no-button* condition was the least effective at promoting interest, compared to the other conditions. However, the other conditions were not highly effective in promoting the beneficial affective paths (ones that led to interest), except for the condition that left it up to the student to choose when to see the progress page (i.e., *button*).

Type of Path		t_0	t_1	t_2	**P(St_0=N)**	**P(St_2)**	**P(P1 OR P2)**	**Likelihood of Path**
Positive (Leads to excited)	**P1**	N	E	E	0.418	0.0004	0.001	(Neg. Affect Path) > (Pos. Affect Path)
	P2	N	N	E	0.418	0.0004		
Negative (Leads to unexcited)	**P1**	N	U	U	0.418	0.0222	0.06	
	P2	N	N	U	0.418	0.0342		

Table 1: Probabilities of a student ending up excited (E) vs. unexcited (U) at t_2 after a two affective transitions for the *no-button* condition.

	no button	*button*	*prompt*	*force*
(1) Positive Affect (Leads to EXC / INT)	.001 / .04	.14 / .10	.12 / .08	.16 / .10
(2) Negative Affect (Leads to Un-EXC/ BOR)	.06 / .18	.02 / .08	.06 / .14	.02 / .14
EXC: Which path is more likely?	NEG > POS	POS > NEG	POS > NEG	POS > NEG
INT: Which path is more likely?	NEG > POS	POS > NEG	NEG > POS	NEG > POS

Table 2. Probabilities of a student finishing in a (1) Positive Affect at t_2 for excited (EXC) or interested (INT); (2) Negative Affect for unexcited (Un-EXC) or bored (BOR). For excited neutral at t_0 is $P(St_0 = N) = 0.418$; for interested, neutral at t_0 is $P(St0{=}N) = 0.503$.

4 Conclusion and Future Work

We explored the utility of a learning dashboard, called the Student Progress Page (SPP), as a form of metacognitive support to alleviate negative affective states (boredom and lack of excitement) and promote the positive affective counterparts. In general, we found that SPP usage was associated with more positive interest in conditions where MathSpring did not prompt for SPP usage – while the opposite pattern was found for the conditions that MathSpring did prompt SPP usage, this was expected given that the prompts were triggered by negative student affect. When considering all four conditions, however, overall we did not find significant differences in terms of affect. This was somewhat unexpected: on the one hand, we know that students are not good at monitoring their own progress, and this can negative affective consequences, so one might expect the conditions that encouraged or even forced SPP usage might improve affect more. On the other hand, however, some theories of motivation argue that having control over ones' activities increases intrinsic motivation, which is related to interest and possibly excitement [17]. When we broke the data down by gender, and considered only the top two SPP conditions (prompt and force), we did find indications of the latter possibility, albeit only for female students, who reported more positive affect (interest) when tailored prompts invited SPP usage than when SPP was enforced. However, the opposite pattern emerged for male students. Given he preliminary nature of this analysis, further research is needed to understand how to design affective interventions taking into account factors related to gender.

Thus far, we have been discussing our analysis related to *overall* affective differences. However, exploring more fine-grained implications of affective interventions is also paramount. This level of explanation was accomplished by analyzing how students transitioned between levels of affective states, such as from bored to excited, as well as how likely certain affective paths were in the four conditions. This analysis focused on affective paths of length two, and in this context, the SPP promoted positive changes towards excitement in students, but was less effective at promoting interest. One possibility for these results is that excitement is a short-term affective state, which would be captured by the short paths we confined our analysis to, while interest might take more time to develop, and so was not captured by the particular length of affective paths we focused on.

In general, our results highlight the utility of having a learning dashboard available but leave questions for how its use should be encouraged. Thus, this is something we will explore in future work. One avenue will involve using talk aloud protocol during students interaction with MathSpring to gather more fine-grained data on students' reactions and affect. A second avenue will employ data mining techniques to further get at student behaviors directly before and after SPP usage and subsequent impact on affect.

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