Collaboration Improves Student Interest in Online Tutoring

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Abstract. Prior research indicates that students often experience negative emotions while using online learning environments, and that most of these negative emotions can have a detrimental impact on their behavior and learning outcomes. We investigate the impact of a particular intervention, namely face-to-face collaboration with a neighboring student, on student boredom and frustration. The data comes from a study with 106 middle school students interacting with a mathematics tutor that provided varying levels of collaboration. Students were randomly assigned to a collaboration or no-collaboration condition. Collaboration was associated with reduced boredom: Students who collaborated more frequently reported increased interest.

Keywords: Affective states · Negative/positive emotion · Collaborative learning · Intelligent tutoring system · Boredom · Frustration

1 Introduction

Key factors that influence students' academic success include their emotions and affective experiences while learning. For instance, student interest has a facilitative effect on cognitive functioning in general [10], and a myriad of positive emotions have an impact on academic performance [19]. Even some emotions traditionally viewed as negative can be beneficial, e.g., confusion is associated with learning under certain conditions [10]. In contrast, the negative affective state of boredom reduces task performance [20] and increases ineffective behaviors within tutoring systems, such as 'gaming the system' [7, 8]. Given increasing recognition of the pivotal role that affective states and predispositions play in learning, developing educational technologies that recognize and respond to student affect is clearly important. To date, however, the emphasis has been on data mining and user-modeling techniques to improve detection of student affect (e.g., [6, 10]). In contrast, less work has focused on assessing and evaluating the impact of interventions to respond to student emotion.

E. André et al. (Eds.): AIED 2017, LNAI 10331, pp. 28–39, 2017.
DOI: 10.1007/978-3-319-61425-0_3

In our research, we have investigated a variety of ways to improve student affect as students work in tutoring systems. In the present paper, we focus on one pedagogical intervention designed to (1) to reduce frustration and (2) promote interest by reducing boredom (which is inversely related to interest [3, 8] and has been shown to be especially detrimental to student learning [5]).

The underlying theoretical framework for our research is based on the Control-Value Theory of Achievement emotions, which states that students' appraisals of control and value are determinants of the emotions that they experience. For instance, boredom is due to a lack of value perceived in relation to the learning activity. There are many ways to increase students' perception of "value" – with the present intervention, we aim to increase "social value", by inviting students to collaborate during their interaction with an intelligent tutor called MathSpring™ (see Fig. 1). Unlike other collaborative approaches with learning technologies that involve collaborating via screen time with remote partners, collaboration in the present study is face-to-face, under the hypothesis that a variety of social cues in the interaction might help students to engage with each other and increase their interest in problem solving.

The target domain is middle school mathematics, a challenging topic for many students. By the time students reach high school, they report boredom and lack of excitement in mathematics at an alarming rate [1]. Thus, there is an important need to address these emotions earlier, e.g., during middle school.

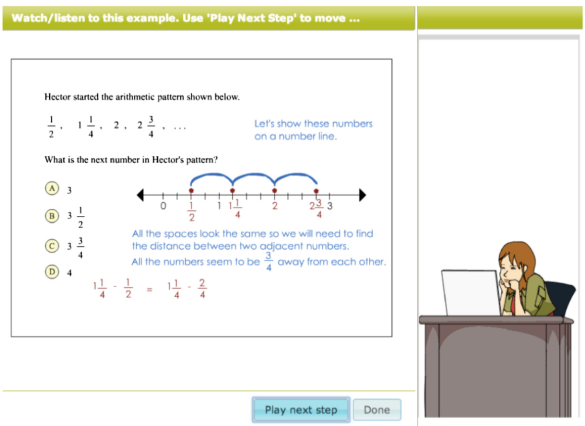

Fig. 1. MathSpring provides math problems aligned to the Common Core Standards in the USA. Scaffolds are provided, such as companions who reflect the student's emotion (bottom, right), hints, animated problems, audio help, worked-out examples, and video tutorials to aid students.

2 Collaboration as a Way to Add Social Value

In traditional classrooms, students often passively absorb topics from teachers, worksheets, and books. Such teaching approaches are marginally effective and produce inert knowledge [29]. Collaboration-based instruction, which is student-centered, differs from traditional teacher-centered approaches because it provides students the opportunity to be active participants in their learning, by explaining to their peers, posing questions, and interacting with one another.

Collaborative learning activities within classrooms have been successful for teaching mathematics [12], both in terms of cognitive and affective outcomes. On the cognitive side, collaboration has been shown to increase achievement in standardized test scores as compared to control groups, with large effect sizes [13, 24]. Moreover, the literature suggests that collaboration can produce in novel ideas and learning gains over and beyond the ability of the best individuals in the group – in other words, collaboration can produce knowledge that none of its members would have produced on their own [14]. Peer-to-peer interactions are vital aspects of collaboration [24, 25], giving students opportunities to question processes, make mistakes, and monitor each other's reasoning.

For the present study, we were especially interested in the affective impact of collaborative learning. Past studies in classroom contexts have shown that collaborative learning has improved student attitudes, such as more altruism and positive attitudes toward classroom life. Collaboration also increases self-esteem, social acceptance, and peer ratings, particularly for students with disabilities [21, 22]. While there is less research exploring the potential of collaboration in online tutoring environments, there are notable exceptions (e.g., [26, 28]) – however, to date research in this area has focused on the cognitive dimension (e.g., learning gains) and not on the impact and effectiveness of collaboration on students' affective states.

Outside the collaboration context, however, there is evidence that tutor features can improve student affect [15]. For example, in our prior work [17], we investigated the impact of providing students access to a dashboard that graphically and textually summarized student performance, e.g., number of problems solved, utility of strategies used, and knowledge gained. While this research did not find an overall impact of this intervention on student excitement, there were indications that the intervention reduced boredom. In particular, the dashboard's utility depended on the way its use was encouraged (either prompted or not prompted).

3 Experiment and Results

The present research was conducted within an established intelligent mathematics tutor called MathSpring™ (see Figs. 1 and 2) [4]. The tutoring system includes a student model that assesses individual student knowledge and effort exerted and adapts the difficulty of mathematics problems accordingly [2]; it also provides hints, tutorial videos and animated worked-out examples with sound played aloud.

For the present research, we extended MathSpring to encourage students to engage in face-to-face collaboration with a neighbor (see Fig. 2). Specifically, MathSpring recorded which student sat next to which student (at login time, students identify neighbors) and subsequently invited students to work together at various times during their interaction with MathSpring – this invitation was provided every eight problems solved or every five minutes, whichever came first. The first student in the pair was free to accept or reject the invitation to collaborate. To increase the likelihood that pairs would work well together, the teacher encouraged pairs who apparently got along well,

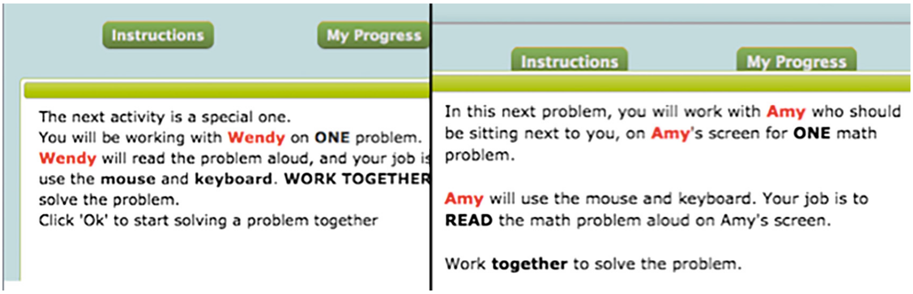

Fig. 2. Collaboration feature in MathSpring invites students to collaborate in problem solving with a peer sitting next to them (a classmate sitting to the left or right). The left screen invites Amy to work with Wendy. Amy might have to wait for a short time untilWendy completes the math problem she is working on ("Waiting for a partner…"). Special roles are assigned to each student to make the collaboration more productive. After students solve the problem together on Amy's screen, they are led back to work on their own computers.

such as friends, to sit next to each other in the classroom, since this can be beneficial for collaboration [18, 23].

3.1 Method

To evaluate the relationship between collaboration and student affect, we conducted a study with students in three 8th grade math classes in a school district in Southern California in the Spring of 2016 ($N = 106$). Students used MathSpring over three consecutive class sessions. Students solved math problems in the following topics: exponents and square roots, expressions, univariate equations, linear functions, angles, triangles, pythagorean theorem and special triangles. On part of the first and last day, students completed pre- and post-affective surveys, which included questions related to affect, including interest and frustration towards mathematics on the pre-survey that provided baseline data on affect. As part of the posttest, questions asked students about their preference towards the collaboration component, if received. Students also filled in pre and post domain questionnaires.

To obtain additional information on affect as students solved problems, MathSpring prompted students to self-report their interest or frustration every five minutes, or after every eight problems, whichever came first, but only after a problem was completed to avoid interruption. The prompts were shown on a separate window and invited students to report on their emotion (interest or frustration). Students could choose to skip self-reporting on their emotion if they wished. Emotion was recorded via a 1–5 point Likert scale (e.g., "*How interested are you feeling right now?*" *Not at all interested (1) somewhat interested (3) extremely interested (5)*). The software cycled through the two emotions and students typically self-reported several times for each emotion.

The experiment used a between-subjects design with two conditions: (1) *no-collaboration* ($N = 57$), where students worked individually, or (2) *collaboration* ($N = 52$), where students were invited by MathSpring to collaborate with a student sitting next to them. In the collaboration condition, MathSpring asked an "initiator" student if he/she would like to collaborate with a partner. If he/she responded affirmatively, MathSpring would wait for the nearby student to finish the problem he/she was working on and then would invite that student to join the "initiator" to work on a new mathematics problem together. Special roles were assigned to each student, to encourage both students to participate at solving the problem. For example, the first student was asked to use the mouse and keyboard and the second student was asked to read the problem aloud on the first student's computer - both students then solved the problem together on the first student's screen (see Fig. 1).

Teachers running the study ensured that students assigned to the collaboration condition generally sat on one side the room, so that students in the control condition were not distracted by their collaborations. Students were randomly assigned to conditions, with the exception of attempting to place students that got along close to each other within the collaboration condition.

Table 1. Pretest measures of math skills, interest, and frustration in math.

	Collaboration N	Collaboration Mean (SD)	Individual N	Individual Mean (SD)
Mathematics Pretest	42	0.09 (0.15)	38	0.11 (0.16)
Interest Pretest	51	2.61 (1.19)	41	2.76 (1.18)
Frustration Pretest	51	3.15 (1.13)	41	2.93 (1.22)

3.2 Results

We first confirmed that the students' baseline affective survey scores and pretest math scores in the experimental and control conditions were not significantly different (see Table 1). Unfortunately, due to a miscommunication in how the pre and posttest should be administered a large amount of data was lost[1]- we ended up with pretest data for $N = 89$ students and posttest data for only $N = 47$ students. In addition, some students simply decided not to answer the math questions in the surveys, leaving blank answers. This lack of posttest data in particular led us to focus on the data within the tutor ($N = 106$ students), and to use pre to posttest changes as a form of 'extra data' to triangulate the findings. In general, differences in pretest results between students in the experimental and control groups were small (*ns*), see Table 1.

Relationship Between Collaborative Learning, Affect and Engagement. We examined the relationship between collaboration and three high-level constructs: learning, affect, and engagement: (1) Learning was assessed through students' gain from pre to posttest on the domain questions; (2) The affective constructs of frustration and interest were measured both through self-reports and pre and post surveys; (3) Engagement was defined as a student's "affective and cognitive state during task

[1] This experiment was run from the other end of the country, which meant we were not able to personally monitor the administration of the tests.

performance as well as performance" [16], obtained from analyzing students' interaction with MathSpring data.

How Are Collaboration and Student Affect Related? To determine the relationship between collaboration and student affect, we obtained a mean value of self-reported *interest* and *frustration* for each student and condition, see Table 2. We measured both of these affective constructs before/after students used the tutor (*pre and post surveys*) and while they worked with the MathSpring tutor (*within tutor*). The sample size in each condition varied somewhat, due to the fact that some students chose not to self-report their affective state. Students reported both less *interest* and less *frustration* within the tutoring environment than they did during pretest questionnaires regarding their overall interest and frustration with math. This is consistent with the findings of Bieg et al. [9] who found that students tended to report less intense affect within a learning environment than they did upon reflection outside of the learning environment.

All students in the control condition had zero collaborations. Students in the experimental condition experienced a range of collaboration activities: students were invited to collaborate from zero to 17 times and students completed collaborations from zero to 14 times ($M = 3.8, SD = 3.3$). Some students collaborated only 1–2 times and so were closer to the control condition in terms of their collaborative experience. It became clear that given the present data, a conventional Analysis of Variance (ANOVA) would not be applicable. Thus, our main analysis consisted instead of partial correlations between total amount of collaboration activities and a variety of outcomes of interest, after controlling for time spent working with MathSpring.

Table 2. Mean affective differences between students in the experimental (Collaboration) and control (Individual) conditions. Measures are *before* use of the tutor (Pretest) and *while* working in the tutor (Within Tutor).

	Collaboration N	Collaboration Mean (SD)	Individual N	Individual Mean (SD)
Pretest **Interest**	47	2.70 (1.16)	45	2.64 (1.21)
Mean **Interest** within tutor	50	2.36 (1.17)	55	2.36 (1.03)
Interest Change from pretest to tutor	45	−0.40 (1.16)	44	−0.38 (1.45)
Pretest **Frustration**	47	3.17 (1.11)	45	2.92 (1.22)
Mean **Frustration** within tutor	48	2.55 (1.18)	53	3.17 (1.11)
Frustration Change from pretest to tutor	44	−0.53 (1.04)	42	−0.47 (1.15)

In our analysis, we accounted for several types of collaboration in order to better understand how students interacted in the collaboration condition (summarized in Table 3). Since the first student in a pair might have to wait for a partner to be ready, MathSpring asked the first student every few minutes if he/she still wanted to wait to begin the collaboration. Table 3 accounts for events in which a student was invited to collaborate (*Invitation*) and completed the collaboration, as well as a split between whether the student was the *First student* or *Partner* for a given completed collaboration. We also tracked the number of times a student waited and the times he/she declined a collaboration.

Table 3 also shows the correlations between student affective and cognitive factors (rows) and collaboration factors (columns) – note that this analysis includes students in the control condition, all of whom had zero collaborations. For example, Row 1 shows a partial correlation between *completed collaborations* and a change in mathematics interest (from pretest to mean self-reported interest while within the tutor), accounting for time spent in the tutor. This suggests that students who collaborated more frequently had a more positive increase in mathematics interest from pre test time ($p < 0.06$). While this is a positive result, a preference for collaboration may be driving the result – students who preferred to collaborate may have accepted more collaboration invitations, and in turn have been more interested than the rest of the students. However, students did not have a choice for collaborations initiated by a neighboring student, and still there is a significant positive correlation between collaborations occurring in the partner's screen and students' boost in interest since the pretest. Thus, we discard that possibility, and conclude that collaboration is positively associated with student interest.

Engagement. Engagement was established based on output from rules embedded in Mathspring to measure that construct. For example, students could elect to "skip" any problem in MathSpring and be given a new problem instead. A student's work on a problem was classified by MathSpring as *disengagement* if the student either immediately skipped the problem to try a new one, or made an attempt in under 4 s after seeing the problem (we considered 4 s as being not enough time to even read the problem, much less to think about how to solve it). Two measures of *engagement* were collected: if a student solved a problem correctly on the first attempt or solved a problem correctly after asking for a few hints.

The significant negative correlation shown in Row 7 of Table 3 suggests that students who received more invitations to collaborate tended to be less *disengaged*. However, because students with high engagement also declined more offers to collaborate, the relationship between collaboration and engagement is not as clear cut.

Students who tended to solve problems correctly on their first attempt (see Row 5) were less likely to be invited to initiate (i.e., host) a collaboration; therefore, unsurprisingly, they were less likely to work on collaborative problems on their own computers (see Column 3). We suspect that these students were going slower and thinking through problems carefully to avoid making mistakes, and thus received fewer opportunities between problems in which they were invited to collaborate. On the other hand, as shown in Row 6, students who tended to solve problems using hints were more likely to receive invitations to collaborate, Column 1 and to work on these problems on their own computers (see Column 3).

Table 3. Partial correlation R values and significance, after controlling for time spent in tutor.

	Invitations to collaborate	Collaborations completed	Collaborations on my screen	Collaborations on second student's screen	'Continue to wait' for a partner	Declines to collaborate per invitation
1. **Interest Change** from Pretest to Inside Tutor (N = 86)	0.04	**0.20**$^{+}$	**0.18**$^{+}$	**0.21***	−0.74	**−0.29**$^{+}$
2. Raw Post-Pre **Interest** (N = 37)	0.18	0.18	0.23	0.08	0.26	−0.17
3. **Frustration Change** from Pretest to Inside Tutor (N = 83)	−0.06	−0.06	−0.05	−0.07	**−0.27**$^{+}$	0.06
4. Raw **Math Improvement** Post-Pre (N = 27)	−0.12	0.14	0.15	0.11	−0.43	−0.34
5. Total **Problems Solved** Correctly on First Attempt (N = 106)	**−0.19***	−0.16	**−0.17**$^{+}$	−0.11	−0.1	−0.05
6. Total **Problems solved** where **Hints** were requested (N = 106)	**0.18**$^{+}$	0.14	**0.17**$^{+}$	0.07	−0.2	0.16
7. **Disengagement Behaviors** – Not reading, or skipping (N = 106)	**−0.17**$^{+}$	0.03	0.03	0.02	0.01	**−0.55****
8. Mean Time to **First Action** (Attempt or Hint) (N = 106)	−0.08	**−0.17**$^{+}$	**−0.17**$^{+}$	**−0.16**$^{+}$	0.02	0.2

$^{+}$Marginally Significant $p < 0.1$, *Significant $p < 0.05$, **Significant $p < 0.01$

Further analyses showed a significant correlation between baseline interest in mathematics problem solving and the number of completed collaborations ($N = 42$, $r = -0.33$, $p < .05$), which indicates that students with lower a priori interest in math problem solving completed more problems in collaborative mode. This helps to explain why students who solved more problems correctly on first attempt also received fewer invitations to collaborate in shared problem solving.

Another result was that students with lower math ability as estimated by MathSpring using within tutor variables accepted more invitations to collaborate ($N = 52$, $r = -.28$, $p < .05$). This confirms our results from [4] that students who are lower achieving prefer additional support (cognitive, meta-cognitive and affective) – in our prior work, provided by interventions such as animated agents, hints, and worked out examples. Thus students who struggled in mathematics accepted more collaboration invitations, which might help explain why students who requested more hints also received more invitations to collaborate.

Student Perceptions About Collaboration. Results from the open questions in the posttest described students' perceptions about the collaboration. There were 26 responses from students in the collaboration condition to the question "*If you worked with a partner, did you like collaborating with your neighbor? Why or why not?*". Seventeen students (65%) reported that they liked collaborating and nine students (35%) reported that they did not.

The qualitative data was examined based on grounded theory methods. First open coding was preformed on the student open-ended responses wherein the coder parsed and reflected on the data with the goal of naming and categorizing phenomena that occur within. A set of four categories was developed that encompassed approximately 80% of the responses. Then the key properties and dimensions of the categories were identified. Next, during axial coding, the coder examined the relationships between the categories, looking to see how they related. Finally, selected coding was preformed, relating the categories and explicating the storyline.

The themes that came up for those who liked the collaboration, regarded **the partner as a helper**, ("*if it is hard math, the other person can help me because they may know something I don't*"); **shared knowledge** ("*It is like there are two different ideas put together to make a big idea*"); **mutual support** ("*they can tell me if they need help or I can ask them for help*"); and **ease** ("*it makes the work easier and faster to finish*").

Additional qualitative research not reported here but carried out in parallel provided further details on the impact of this collaboration on students' enjoyment and learning [27]. Specifically analysis of videos and surveys suggest that collaboration encouraged students to work together and to enjoy the experience, even though students might not necessarily have followed the prompt scripts to play the roles they were assigned.

3.3 Discussion and Future Work

The present research evaluated the relationship between collaboration and students' emotion and demonstrated that collaboration can counter boredom. Specifically, the more collaborations students completed in the tutoring session, the higher their interest in solving math problems, after accounting for baseline interest before tutoring. The following factors were significant predictors of student improvement in interest: number of collaborations completed, number of collaborations originated on the partner's screen, and number of collaborations originated on the individual's screen (marginal). Students who started off with low interest worked collaboratively more often; in the end, students who needed to boost their interest more also benefited most from the collaboration. Students' reported less frustration within the tutoring environment than they did during pretest questionnaires, but we did not find a clear relationship between collaboration per se and frustration. Results from open-ended survey questions after the tutoring session was completed revealed that students' perceptions about collaborative problem solving activities indicate added social value.

Two measures of engagement were collected: solving a problem correctly on the first attempt or solving a problem correctly after asking for hints. Students who tended to be more disengaged also received more invitations to collaborate, as they were going faster, and more collaboration invitations were accrued in between math problems, every 5 min or 8 problems. In addition, these students declined significantly fewer offers to collaborate. Additionally, students who solved problems on their first attempt were less likely to receive invitations to collaborate, which likely led them to originate and decline fewer collaborations.

According to the Control-Value Theory of emotion [19, 20], boredom is an emotion originated in low value appraisals of the learning task, while frustration is related to low perceived control over the learning task. We hypothesized that inviting students to engage in face-to-face collaboration would provide added *social value* to solving math problems; we did not hypothesize that collaboration might be a tool to place a student in greater control over the learning task. We did expect that collaboration would be associated with increased student interest but not necessarily reduced student frustration. According to the control-value theory, frustration should be resolved by increased control, and not necessarily by adding social value. Our results are in line with these predictions: we found no evidence that collaboration reduced student frustration, and we did find that student interest increased with increased collaboration. The qualitative data helped to support the claim that the reason for the boost in student interest was due to the added value associated with socially sharing knowledge and support.

In terms of future work, we intend to investigate whether our measures of student behavior occur within collaboration problems or as a result of more collaborations taking place. In other words, collaboration may impact student behaviors *during* collaboration vs. *after* collaboration. Distinguishing among these possible scenarios requires further analysis, focusing on finer grain interactions in which data has not been aggregated across all students. Particularly, there are two conflicting causal hypotheses for the results. First, students who solve problems quickly may have more opportunities to collaborate, because collaborations do not interrupt students as they work on a problem and occur only after a math problem is completed. Conversely, when students do collaborate on a problem they may spend time conferring with their partner rather than seeking help from MathSpring; they may be more cautious and methodical in their attempts as well given that they must now reach consensus. These two possible explanations may be at odds: working faster makes collaboration more likely and collaboration itself may slow students down. Distinguishing among behaviors within collaborative problem solving against individual problem solving, for students in the collaboration condition, may help clarify this.

In addition, we acknowledge that various factors may impact the success of collaboration (e.g., preference for collaboration, placing two bored students together might not work, etc.). In future work we will explore these factors and fine-tune when and how students should be invited to collaborate. We also plan to investigate student affect using a finer granularity, to shed light on how students transitioned among affective states (e.g., can collaboration help students become "unstuck" from a state of disinterest/boredom). Addressing this question requires information on student affect more frequently than is provided by the self-reports. One solution to this involves could the construction of student models that can provide frequent predictions of student affect (e.g., interest). These various avenues await future research.

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