Modeling Frustration Trajectories and Problem-Solving Behaviors in Adaptive Learning Environments for Introductory Computer Science

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Abstract. Modeling a learner's frustration in adaptive environments can inform scaffolding. While much work has explored momentary frustration, there is limited research investigating the dynamics of frustration over time and its relationship with problem-solving behaviors. In this paper, we clustered 86 undergraduate students into four frustration trajectories as they worked with an adaptive learning environment for introductory computer science. The results indicate that students who initially report high levels of frustration but then reported lower levels later in their problem solving were more likely to have sought help. These findings provide insight into how frustration trajectory models can guide adaptivity during extended problem-solving episodes.

Keywords: Frustration trajectory· adaptive learning environments· problem-solving behavior· computer science education· block-based programming.

1 Introduction

Affect plays a critical role in human behavior, social interaction, and learning [4, 6]. Learners can benefit from affective states such as engaged concentration, while disengagement and boredom can lead to negative learning outcomes [1, 7]. An affective state of particular interest is frustration, which can occur when a learner experiences an impasse or encounters task errors [5]. While repeated frustration can lead to boredom [9] and eventually attrition [8], many studies show that a certain level of frustration can motivate a learner to overcome obstacles during problem solving and can benefit learning [14, 16, 17].

Modeling student frustration presents significant challenges because frustration is dynamic in nature that has a complex relationship with learner behaviors. In computer science learning in particular, students engage in an iterative process of task planning, implementation and testing [5]. Students learning to code may experience more intense and durable frustration than students using highly-scaffolded learning environments [13, 18]. Learning environments informed by dynamic changes in frustration could prevent a learner from experiencing prolonged frustration.

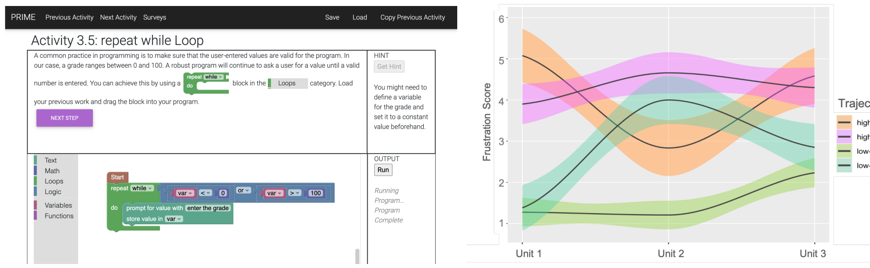
This paper investigates the role of learner frustration trajectories in an adaptive, block-based programming environment. Using frustration trajectories generated from learner self-reports, we investigate two research questions: 1) What common trajectories of frustration arise over problem-solving interactions with a block-based programming environment? 2) Do students with different frustration trajectories display different problem-solving behaviors? We identified four distinct frustration trajectories over a series of programming activities, and found that learners' problem-solving behaviors exhibited significant differences across different phases of interactions. These findings can inform the design of adaptive learning environments to promote productive frustration and better optimize individuals' learning experiences.

2 Study

This study utilized a dataset collected from student interactions with a block-based programming environment, Prime (Fig. 1. (a)), designed for undergraduate introductory computer science to teach basic programming concepts. Students proceed through 20 programming activities over three units. Each unit contains 6 or 7 activities and is designed to be completed in approximately an hour. In the system, students can request hints (top-right panel) for a specific step of a programming problem. More details on the learning environment can be found in our previous work [10, 20].

Participants are students in an introductory computing course at a university in the southeastern United States. Students completed a pre-survey about their prior programming experiences, CS attitudes and CS concept assessments (as pre-test) [15]. These student incoming characteristics (pre-test scores, CS attitudes and prior programming experiences) were used as covariates in our following analysis (RQ2). During the learning activities, at the end of each unit, students responded to a seven-item Likert questionnaire [19], which included the question, "I was frustrated while working on this unit." We used student responses to this question collected from each of the end-of-unit surveys as the measurement of frustration. The data used in this paper includes 86 students who attempted at least one activity in each unit and completed all pre-, post-, and end-of-unit surveys, with 67.4% majoring in Computer Science or Computer Engineering. Students attempted a mean of 19.4 programming activities ($SD =$ 1.8, $Median = 20$) and completed 15.8 ($SD = 4.8$, $Median = 18$).

The Prime learning environment logs interaction events. We grouped five frequent interaction events into two problem solving behaviors. *Workspace exploration* involves four events, namely creating blocks, moving blocks, deleting blocks and searching through the toolbox. *Help-seeking* indicates the frequency of students pressing the hint button while solving problems. We calculated all variables as standardized values per Prime instructional unit with a mean of 0 and standard deviation of 1.



a. b.

Fig. 1. (a) Block-based programming environment (b) Frustration trajectories

3 Results and Design Implications

RQ1: Frustration trajectory clustering. The average frustration reported across all units was 3.18 out of 7 (SD = 1.97). Over the course of the programming activities, students' reported frustration increased, with a mean of 2.71 after Unit 1, 3.29 after Unit 2 and 3.52 after Unit 3 (SD = 1.88, 2.02, 1.93, respectively). A paired-sample t-test revealed significant change from Unit 1 to Unit 2 ($p = .006$), but no significant difference from Unit 2 to Unit 3 ($p = .259$). To cluster learners' frustration trajectories, we considered both the initial intensity and relative changes of frustration. The clustering vectors were composed of the following features: 1) binary frustration level during Unit 1, split by the median ($Median = 2$); 2) relative frustration changes from Unit 1 to Unit 2; and 3) relative frustration changes from Unit 2 to Unit 3. We performed a k-medoids [11] clustering of learners' frustration and used the distortion elbow [12] to visually determine the optimal number of clusters: four. We refer to the four clusters as *low-equal* (33.7%, 29/86), *low-up* (24.4%, 21/86), *high-up/equal* (27.9%, 24/86) and *high-down* (14%, 12/86). Fig. 1. (b) shows the frustration trends of the four clusters, two groups with low frustration and two groups with high frustration at the end of the first unit. Among the two low-starting groups, one group (*low-equal*) remained relatively constant over the entire interaction, $M(SD)_{Unit1,2,3}$ = 1.28 (0.45), 1.21 (0.41), 2.40 (1.74), whereas the other group (*low-up*) whose frustration went up dramatically after Unit 2 and moved slightly down after Unit 3, $M(SD)_{Unit1,2,3}$ = 1.38 (0.50), 4.29 (1.62), 3.05 (1.83). For students who were highly frustrated after Unit 1, one group (*high-up/equal*) was constantly frustrated over time, $M(SD)_{Unit1,2,3}$ = 4.42 (1.43), 5.15 (1.26), 4.75 (1.62), while the other group (*high-down*) became less frustrated in the middle and went up at the end, $M(SD)_{Unit1,2,3}$ = 5.08 (0.86), 2.83 (1.40), 4.58 (1.16).

RQ2: Frustration trajectory and problem-solving behaviors. To investigate whether learners in different frustration trajectories exhibit different frequencies of problem-solving actions, we conducted a one-way MANCOVA to compare the effect of frustration trajectories on *workspace exploration* and *help-seeking* in three units after controlling for student incoming characteristics (described in section 2). The results revealed a statistically significant effect of frustration trends ($F(18,\ 209.789) = 2.491$, p =.001, Wilks' Λ = .578, partial η^2 = .167). Post-hoc tests to determine each dependent variable effects revealed that *workspace exploration* and *help-seeking* in Unit 2 are significantly different between the frustration trajectories.

Next, we conducted pairwise comparisons on estimated marginal means of dependent variables in each activity to test between-group differences. The results showed that the *low-equal* group performed a relatively low number of programming actions (*workspace exploration* and *help-seeking*) throughout. The *low-up* students had the highest number of *workspace explorations* (*M(SD)* = 0.64(0.99)) in Unit 2 where their frustration increased. The frequency of *workspace explorations* performed by the *low-up* group was significantly higher than all other groups. Interestingly, the *high-down* group, whose frustration decreased in Unit 2, were frequent help-seekers across all three units (*M(SD)*$_{Unit1,2,3}$ = 0.74(1.79), 0.81(1.84), 0.22(1.84)). They requested significantly more hints than the two early-low groups in Unit 1, and more than the all three other groups in Unit 2. The results also indicated that while the group with persistent frustration (*high-up/equal* group) conducted an average level of *workspace exploration* in Unit 1 (*M(SD)* = 0.26(1.32)), these students made the lowest number of *workspace exploration* actions in Unit 2 (*M(SD)* = -0.55(1.05)) and Unit 3 (*M(SD)*= -0.45(0.87)) and were significantly lower than *low-up* group in Unit 2 and the *low-equal* group in Unit 3.

Design implications. A low rate of *workspace exploration* behaviors may significantly predict students' frustration. For previously non-frustrated students (*low-equal*), scarcity of these actions is likely indicative of a smooth progression, and for previously frustrated students (*high-up/equal*), it is more likely a sign of disengagement. This suggests that to accurately detect frustrated learners, it is important to take prior frustration states into account. This finding aligns with prior work indicating frustration could lead to lack of persistence and result in systematic guessing and gaming behaviors [3].

Students with a *high-down* frustration trajectory sought more help by requesting hints. This suggests that providing additional hints and feedback may help close the gap between task difficulty and user knowledge, thus reducing learner's frustration. Another possible solution would be to provide guidance to students on managing their frustration and introducing relevant strategies (e.g., help-seeking). It is important to note that learning environments should not be designed to entirely eliminate frustration, as frustration is inherent in learning, particularly when students encounter challenging problems [2]. Rather, learning environments should be designed to enable students to experience productive levels of frustration by recognizing and regulating it.

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