

Personalized Affective Feedback to Address Students' Frustration in ITS

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Abstract—The importance of affective states in learning has led many Intelligent Tutoring Systems (ITS) to include students' affective states in their learner models. The adaptation and hence the benefits of an ITS can be improved by detecting and responding to students' affective states. In prior work, we have created and validated a theory-driven model for detecting students' frustration, as well as identifying its causes as students interact with the ITS. In this paper, we present a strategy to respond to students' frustration by offering motivational messages that address different causes of frustration. Based on attribution theory, these messages are created to praise the student's effort, attribute the results to the identified cause, show sympathy for failure or obtain feedback from the students. We implemented our approach in three schools where students interacted with the ITS. Data from 188 students from the three schools collected across two weeks was used for our analysis. The results suggest that the frustration instances reduced significantly statistically ($p < 0.05$), due to the motivational messages. This study suggests that motivational messages that use attribution theory and address the reason for frustration reduce the number of frustration instances per session.

Index Terms—Intelligent tutoring system, affective states, affective feedback, personalized feedback, responding to frustration, reasons for frustration.

I. INTRODUCTION

AN Intelligent Tutoring System (ITS) provides personalized learning content to students based on their needs and preferences. An ITS consists of the learning content, the learner model, and the adaptation engine. Learner models are constructed from the log files available in the ITS. The students' interaction with ITS, such as responses to questions, the number of attempts at a task, and the time taken for various activities (such as responding or reading) are captured in the ITS log file. Learner models also typically contain information such as the students' previous knowledge and background [1], from which it is possible to infer the students' cognitive states.

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The adaptation engine personalizes the learning content based on the data from the learner model. It is now well established that the learning process involves both cognitive and affective processes [2], [3], and the consideration of affective processes has been shown to achieve higher learning outcomes [4], [2]. The importance of a student's affective component in learning has led ITS to include students' affective states such as frustration, boredom, confusion, flow, curiosity, and anxiety in their learner models. In this research work, we focus on the response to students' frustration.

Current research on detecting frustration includes students' self-reported data of their affective state [5], [6], mining the system's log file [7], face-based emotion recognition system [8], analyzing the data from physical sensors [5], and using sensing devices such as physiological sensors [9]. Responding to frustration involves listening to the person who is frustrated without reacting or interrupting [10] and by providing opportunities to express their emotions [4]. In educational systems, frustration has been addressed by providing feedback delivered using agents [11], [12]. The agents display the motivational messages to address the negative consequences of frustration [4], [11], and [12]. The agents are designed to show empathy and encourage the students to continue learning.

In this research work, to detect (recognize) students' frustration, we follow a theory-driven approach [13], in which we construct a model for students' frustration using log data of their interaction with the ITS. This model is based on theoretical definitions of frustration [14], and is formed by selecting and appropriately combining the features in the ITS log file that predicts a student's frustration. The model helps us understand the contribution of each feature towards the student's frustration. Hence this approach provides us information not only of when the student is frustrated but also why the student is frustrated. This leads to an informed adaptation while responding to students' frustration by creating and displaying personalized motivational messages as feedback.

We implemented and evaluated our approach to responding to students' frustration in a large-scale commercial math ITS called Mindspark [15]. We integrated the theory-driven model [13] in Mindspark, to detect students' frustration in real-time as they work with the ITS. To respond to students' frustration, we developed motivational messages based on the identified reasons for frustration and data from Mindspark log files. We used attribution theory [16], praising student's effort [17] and showing empathy [4], to create and display the motivational messages.

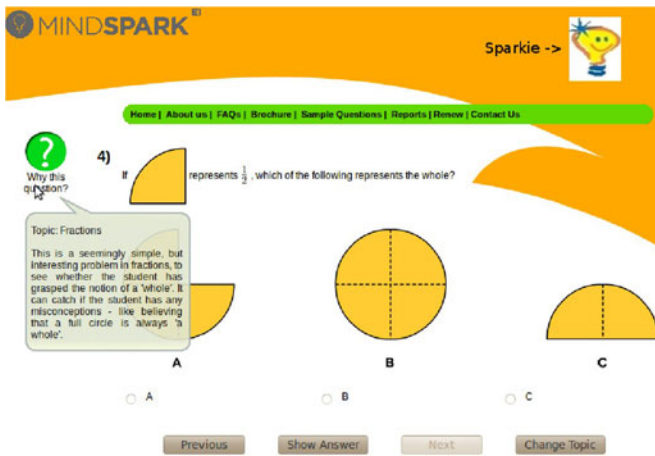


Fig. 1. A sample question from Mindspark on Fractions. Sample image of Sparkie is shown at the top-right corner of the figure.

Further, we developed an algorithm to show the motivational messages whenever the student is detected as frustrated. To evaluate our approach, we analyzed the number of frustration instances per session after implementing the algorithm. The instances of frustration showed a statistically significant reduction ($p < 0.05$), after displaying the motivational messages.

This paper is organized as follows. We describe the system used in our research, Mindspark, in Section 2. Related work is reviewed in Section 3. The theory-driven model to detect frustration and the theoretical definitions considered in our approach are discussed in Section 5. Implementation of our approach, to detect and respond frustration, in Mindspark is described in Section 5. In Section 6, our strategies and algorithms to respond to frustration are detailed. Data collection methodology and results of our approach are given in Section 7. This research work is summarized and concluded in Section 8.

II. SYSTEM: MINDSPARK

Mindspark, a commercial mathematics ITS developed by Educational Initiatives India (EI-India)¹, is used in our research to implement and test our approach to respond to frustration. Mindspark has been incorporated into the school curriculum for different age groups (grades 1 to 10) of students [15]. Mindspark is currently implemented in 100 schools and is being used by 80,000 students on an average of four sessions per week, with each session ranging from 25 to 30 minutes.

Mindspark is a computer based self-learning system, in which students learn mathematics by answering questions posed by the system. Mindspark provides detailed feedback and an explanation upon receiving the answer from the student. A sample question from Mindspark is shown in Fig. 1. Mindspark consists of a sequence of specially designed learning units (clusters), which contain questions on concepts that make up the topic. Each topic consists of questions of progressively increasing levels of complexity. Mindspark covers a

wide range of topics in school level mathematics such as linear inequalities, matrices, quadratic equations, fractions, decimals, and polygons. Mindspark adaptation logic selects the questions to be presented based on a student's answer to a previous question and his/her overall performance in the topic, which allows the student to move at his/her own pace. If a student performs poorly in the current topic (for example, the student does not answer sufficient number of questions correctly), s/he will be moved to a lower complexity level in the same topic. In Mindspark, if a student answers three consecutive questions correctly, s/he receives a Sparkie (extra motivational points), shown in the Fig. 1 at the top-right corner. If a student answers five consecutive questions correctly, then s/he receives a Challenge Question (tougher question from higher complexity level). If the student answers the Challenge Question correctly, s/he receives five Sparkies. Every week, the highest Sparkie collectors (Sparkie Champ) are identified and their names are published on the Mindspark website².

Typically a student spends 25 to 30 minutes in each Mindspark sessions solving 30-40 questions. The students' interactions with Mindspark are recorded in a log file. The log file contains the following information: user ID, session ID, date, question number, topic code, the answer provided by the student, time taken to answer, result, and the time is taken to read the explanation.

The features of Mindspark, such as, feedback with an explanation, adapting questions based on the students response and logging of the students' response, the time is taken to answer and other common data are available in most of ITS. Mindspark is used as part of regular school curriculum and has data of more than 80,000 students. Thus it provided us an opportunity to implement our approach and test it with real-time interactions of students.

III. RELATED WORK

The review paper [18] discusses the research works in responding to learners' affective states. In this section, we focus on the systems (ITS and Educational games) which detect and address the students' affective states while they interact with the system. We describe five such systems in this section.

To study the effect of three types of responses to frustration—ignore students' frustration, collect feedback from students, and provide messages—an affect-support computer game [4], induces frustration by freezing the screen when the students play the game. The first type "Ignore students' frustration" provides no motivational messages and does not collect feedback from the users. The second type "Collect feedback" collects the student feedback in terms of how they feel, but and does not provide any motivational messages. In the third type, the system provides feedback messages and sympathy messages whenever the user reports frustration. The impact of responses provided to the students was analyzed using data from 71 students. Students' frustration is identified by self-reporting using questionnaires. According to the reported analysis, students felt significantly less frustrated

¹<http://www.ei-india.com/>

when playing the game without freezing than the game playing with freezing. The students who got feedback message and empathy messages played the game for significantly more time than the students who got no messages implying that responding to frustration by providing motivation has an impact on students' frustration.

Scouter the Tutor is an ITS to teach how to create and interpret scatter plots of data [19]. Using students' interaction with the system this system detects when a student cheats the system to complete the assigned task by exhausting all the hints provided (game the system). If the student games the system, the agent (Scouter) shows empathy towards the student with expressions and motivational messages like "student should work in order to learn." If the student does not game the system, the agent shows happy expressions and occasionally provide positive messages. This system was tested using 124 students. The students were divided into control and experimental groups. Students' affective states like boredom, frustration, and confusion were observed using human observers while they interacted with the ITS. This system reported that no significant difference between the control and experimental groups in the observed affective states. However, the students reported liking the agent.

Wayang Outpost [2], is an interactive ITS used to teach math to school students. This system used physiological sensors to detect affective states. The data from the sensors were applied to data-mining tools to detect the affective states such as confidence, excitement, boredom, focus, frustration, and anxiety. Based on the detected affective states, this system provides delayed or immediate feedback. The agent reflects the predicted student's emotion and provides motivational messages created based on Dweck's [17] motivational message theory—praise the effort instead of the result. The preliminary analysis of this system was tested using 34 students' interaction with Wayang Outpost. This system reported that the students changed their engagement (from low to high) with the system.

MathSpring [20], is an ITS for mathematics that personalizes math problems. Students self-report the emotions in a five minutes interval. Based on their self-reported emotions, the empathic messages were shown to the students. Learners' emotional states are responded using agents that show the empathic messages either visually or verbally. The preliminary results of the system using data from 37 students' shows that the empathetic messages improve student's learning and reduce their anxiety.

In a recent research work [21], the learners' frustration that is detected while they interact with TC3Sim, a serious game for training tactical combat casualty care skills, were responded using motivation feedback messages. Learners' frustration is detected using log data collected from learners' interaction with TC3Sim and applied to the linear regression model. The motivation feedback messages are created using three motivational theories, and its effect is analyzed. The results of data from 124 participants show that motivational feedback intervention designed using self-efficacy theory [22] is associated with the better learning.

In existing systems, four different approaches (self reporting, human observation, data-driven classifiers, and data from physiological sensors) have been used to detect affective states. To address students' affective states such as frustration, existing systems have used agents to display messages or to ask students to reflect their emotions. These systems report that addressing frustration positively influences the student's learning—in areas such as increased time of playing the game, reduction in anxiety, better learning or change in student engagement with the system.

In this research article, we used the theory-driven approach [13] to detect frustration with reasons for the affective state. The feedback messages are developed to address the reasons for frustration and delivered using an agent. Our proposed approach to detect and address the frustration instances is implemented in actual schools as part of their curricula. We analyze the effects of personalized motivational messages on the number of frustration instances in ITS.

IV. THEORETICAL BASIS

In this section, we briefly describe our theory-driven approach to detect frustration and the theoretical basis of our research to respond to frustration.

A. Detecting Frustration

We developed a model to detect students' frustration while they interact with an ITS [13]. The model is derived from a theoretical definition of frustration [14]. The definition of frustration was operationalized for the ITS log file and new features were constructed. The constructed features are used to form a linear regression model to detect frustration.

In this approach, the selection and the combination of features from the ITS log file were done via a systematic process based on an analysis of goal-blocking events. Guided by the theoretical definition, the goals of the student with respect to their interaction with the ITS was first identified, and the top n goals were selected. Based on information from the student log, a blocking factor, bf , for each of the n goals was identified. A linear regression model for F_i , the frustration index at i th question, based on the blocking behaviors of student goals was formulated. The threshold to the frustration index was applied to detect whether the student is frustrated or not. The weights of the linear regression model were determined during training process with labeled data from the human observation, an independent method to identify affective states.

The model to detect frustration from [13] is reproduced

$$F_i = \alpha[w_0 + w_1 * goal1.bf + w_2 * goal2.bf + w_3 * goal3.bf + w_4 * goal4.bf + w_5 * t_i] + (1 - \alpha)[F_{i-1}]. \quad (1)$$

In the above equation $w_0, w_1, w_2, \dots, w_n$ are weights, which are determined by linear regression analysis. The terms $goal1.bf, goal2.bf, \dots, goaln.bf$, are the blocking factors for goals $goal1, goal2, \dots, goaln$, respectively. The term t_i , the

time spent by the student to answer the question i . The last term in the equation, $(1 - \alpha)[F_{i-1}]$ accounts for the cumulative effect of frustration. The value of α , determines the contribution of frustration at $((i - 1)$ th) question to frustration at i th question, α ranges from 0 to 1. The theory-driven model helps us to understand the contribution of each feature towards the reasons for the student's frustration.

We created, validated, and applied an observation protocol based on FACS, and collected the real-time classroom data of 27 students of class six. We recorded 932 observations from 27 students. The training datasets were used to learn the weights of the frustration model. The gradient descent method was used to calculate the weights of the model. The trained model was tested using the test dataset. The frustration model detected student's frustration from Mindspark log data with accuracy = 88%, precision = 78%, recall = 33%, Cohen's Kappa = 0.31, and F1 score = 0.46. To compare the performance of existing data-mining approaches on the Mindspark log data, several features were constructed from the log file without application of theory; the selected features were applied to the different classifiers to detect frustration. The results of our approach are relatively equal compared to existing approaches and in addition the cause of frustration is clearly seen, since we can infer which feature contributes more towards frustration.

B. Theoretical Basis for Responding to Frustration

We respond to students' frustration using motivational messages. Motivational messages encourage the student to continue the task instead of dropping out due to frustration or goal-failure [23].

We now discuss the motivation theories we used to create our messages.

For the past 3 decades, the dominant theory of motivation is Attribution theory. Attribution theory is widely used in education research [24], [25], especially in ITS, to address the students' affective states [26], [27].

1) *Attribution Theory*: Attribution theory considers humans as researchers who are trying to understand the world around them using their own techniques, to reach logical conclusions. Attribution theory, when applied to motivation, considers the person's expectation and the response from the event. Attribution theory was first constructed by Heider [28] and subsequently developed by Weiner [16] and relates emotional behaviors with academic success and failure. The causes of success and failure related to achievement context are analyzed and the reaction of the person is related to the outcome of an event. That is, a person feels happy if the outcome is successful and frustrated or sad if the outcome of the event is a failure. This is termed as "outcome dependent-attribution independent" [16]. The student's attribution of success or failure is analyzed in three sets of characteristics: locus (location of cause), stability (students performance in the future), and controllability (factors which are controllable by the student and have the ability to alter them).

Attribution theory implies that the person's attribution towards success or failure contributes to the person's effort on

future activity. If the student attributes the success to internal and stable factors then it will lead to pride and motivation. If the student attributes the failure to the internal and stable factors then it will lead to diminishing the self-esteem, shame, and anger. Hence, in our research we motivate the students' failure by messages which attributes the failure to external or unstable or controllable factors will help them to set a new goal with self-motivation.

In our research, in addition to the attribution theory we use Klein *et al.*'s guidelines [4] to respond to affective states and Dweck's research [17] on feedback messages. Klein *et al.*'s guidelines in [4] to respond to affective states are a) the system should provide the option to receive the feedback from the student for their affective state b) The students' feedback should be requested immediately whenever the student is detected frustrated and c) The system should provide feedback messages with empathy, which should make the student feel that s/he is not alone in that affective state. Dweck's research [17] on feedback messages to praise the students' effort instead of the students' intelligence indicates that the students who were praised for effort displayed more enjoyment in solving difficult problems.

In next section, we explain the methodology to detect and responding to frustration in Mindspark.

V. IMPLEMENTATION IN MINDSPARK

The block diagram of the methodology to detect and responding to frustration is shown in Fig. 2.

Students' interactions with the Mindspark user interface, step 1 in Fig. 2, are stored in the log file.

The definition of frustration [14] (step 3) was operationalized for Mindspark log data and new features were constructed (step 4). Then we apply the Equation (1) from Section 4.1, to detect frustration in step 5. If the student's frustration instances is detected, then the reasons for frustration from the model is extracted, step 6. The source of frustration are represented as events. Once the frustration is detected, the messages to respond frustration, step 7, are created using attribution theory. The appropriate motivational message based on the events and the data from log file is selected, step 8, as explained in the Section 6.5, and displayed to the students.

The implementation of theory-driven model to detect frustration (steps 2-5) in Mindspark is explained below.

A. Detect Frustration in Mindspark

In order to detect frustration in Mindspark, we extract the following parameters from the log data, step 2 in Fig. 2.

Data Required

- a_i , the student's response to Mindspark's current question.
- S , Time spent to answer the current question.
- Question type, challenge or normal.

$a_i = 1$ if correct, $a_i = 0$ if wrong.

a_{i-1} is result of last question .

a_{i-2} is result of $(i - 2)$ th question. And so on for, $a_{i-3}, a_{i-4}, a_{i-5}, \dots$

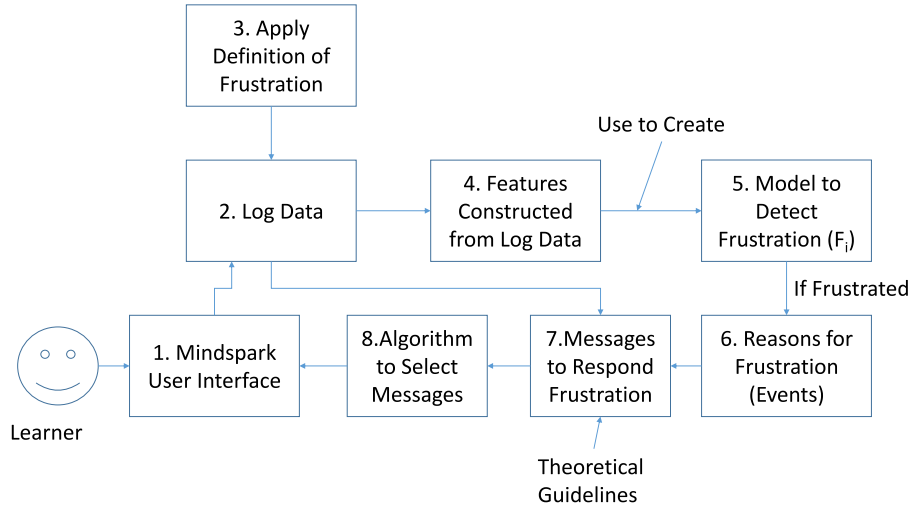


Fig. 2. Block diagram of our methodology to detect and responding to frustration in mindspark.

Using the data from the log file, the goal blocking factors $goal.bf$ are calculated (step 4). The goal blocking factors (features) are used to calculate the frustration index, F_i , using the Equation (1). The frustration model was trained using the data collected during human observation. In step 5, the test data was applied to the trained model and classified as frustration or non-frustration based on a threshold value as described in our previous research work [13].

B. Our Approach to Respond to Frustration in Mindspark - Overview

Steps 6-8, in Fig. 2 summarize our approach to responding to frustration. In Step 7, we create the messages to respond to frustration based on the reasons for frustration (step 6). To create motivational messages we developed theoretical guidelines based on literature, identified reasons for students' frustration and data from the log file. In Step 8, we develop and apply an algorithm to display the motivational messages. Steps 6-8 is detailed in next section. The impact of our approach to responding to frustration is evaluated and explained in following sections.

VI. CREATING MESSAGES TO RESPOND TO FRUSTRATION

As described in previous section motivational messages are developed based on reasons for frustration, theoretical guidelines, and data from the log file.

TABLE I
STUDENT GOALS AND BLOCKING FACTORS FOR MINDSPARK

Student Goal	Blocking factor
$goal1$: To get the correct answer to the current question	$goal1.bf$: Answer to the current question is wrong
$goal2$: To get a Sparkie (answer 3 consecutive questions correctly)	$goal2a.bf$: Answers to previous two questions are correct and to current question is wrong $goal2b.bf$: Answer to previous question is correct and to current question is wrong

A. Reasons for Frustration

The prime reason for frustration is goal failure [13]. The possible reasons for goal failure are identified from the students' goal while they interact with the ITS. We represent these reasons as "events." To create and display the messages we consider these events in Mindspark. We modified the frustration model to identify the reasons for frustration (RoF) as shown.

$$RoF = goal1.bf + goal2.bf + goal3.bf + goal4.bf. \quad (2)$$

The goals $goal1$, $goal2$, and the corresponding blocking factors $goal1.bf$, $goal2.bf$, are given in the Table I. To model the blocking factor (bf) of each goal, we consider students' response, a_i , a feature captured in Mindspark student log file.

List of $goals$ and its corresponding blocking factor $goal.bf$ while working with Mindspark is detailed in [13], however we explain $goal2$ and its corresponding blocking factor $goal2.bf$ below as example to calculate values of RoF . The values of RoF and its corresponding reasons for failure are detailed in Table II. The value of RoF will be in the range of 0 to 5.

For $goal1$ of "to get the correct answer to the current question" the blocking factor is getting the wrong answer to the current question. We use a_i to represent the answer to the current question; $a_i = 1$ if correct, $a_i = 0$ if wrong. The blocking factor of $goal1$ is captured using:

$$goal1.bf = (1 - a_i) \quad (3)$$

For $goal2$, "to get a Sparkie" the student should answer three consecutive questions correctly. This goal can be blocked if a student gets any question wrong in a sequence of three questions. The blocking factor by getting the wrong to current question is addressed in $goal1.bf$, hence we consider only the blocking factor by getting the second and third answer wrong in a sequence of three question. $goal2.bf$ has two components: One way in which $goal2$ can get blocked is, if the student answers first two questions correctly in a sequence of three

TABLE II
EXPLANATION OF THE REASONS FOR GOAL FAILURE - EVENTS

Event	RoF Value	Answering Pattern
E1	0	The student's response to current question, a_i , is correct
E2	1	The student's response to current question, a_i , is wrong Normal and Challenge both
E3	2	The student's response to current question, a_i , is wrong and to previous question, a_{i-1} , was correct
E4	3	The student's response to current question, a_i , is wrong and to two previous questions, a_{i-2} and a_{i-1} , were correct
E5	4	The student's response to current question, a_i , is wrong and to three previous questions, a_{i-3} , a_{i-2} and a_{i-1} , were correct
E6	5	The student's response to current question, a_i , is wrong and to four previous questions, a_{i-4} , a_{i-3} , a_{i-2} and a_{i-1} , were correct

questions and the third question wrongly. This is captured by blocking factor $goal2a.bf$:

$$goal2a.bf = (a_{i-2} * a_{i-1} * (1 - a_i)). \quad (4a)$$

The second way in which $goal2$ can get blocked is, if the student answers only the first question correctly in a sequence of three and the second question wrongly. This is captured by blocking factor $goal2b.bf$:

$$goal2b.bf = a_{i-1} * (1 - a_i) \quad (4b)$$

The blocking factor of $goal2$:

$$goal2.bf = goal2a.bf + goal2b.bf \quad (5)$$

In the Table II, events E3 and E4 are corresponding to the $goal2.bf$. Event E4 occurs if the student's response to current question is incorrect and the response to two previous questions are correct. That is the student's goal of getting three consecutive questions correct ($goal2$), in order to receive a Sparkie, is blocked by the wrong answer ($goal2a.bf$) in the third question. Substituting the values of a_i , a_{i-1} , and a_{i-2} in Equations (3) and (5), the values of $goal1.bf$ is 1 and $goal2.bf$ is 2. The corresponding RoF values using the Equation (2) is 3.

B. Strategies Used to Create Motivational Messages

The content in our motivational messages is based on strategies recommended in existing literature and attribution theory [16]. Attribution theory implies that motivating students' by messages which attribute the failure to external factors (such as math, the difficulty of the question) will motivate them to set a new goal. We request feedback from a student after detecting frustration and displaying feedback messages to show empathy for students' affective state. Using the recommendation from [11], [12] our motivational messages are displayed using the agents who communicate empathy in their messages. Based on above recommendations, we create motivational messages whose goal is:

- To attribute the students' failure to achieve the goal to external factors [16].
- To praise the students' effort instead of outcome [17].
- To show empathy, to make the student feel that s/he is not alone in that affective state [4].
- To request students' feedback [12].

The messages are displayed messages using an agent [11], [12]. In addition to the above strategies we consider the identified reasons for frustration (during detection) while creating the messages.

C. Data from the Log File

In addition to the strategies and the reasons for frustration discussed above, the data from the Mindspark log file is also considered to create the motivational messages. The following parameters are identified from the Mindspark log data, which are considered while creating the motivational messages.

- Average Response Time (*Res Time*) is the average time taken to answer the questions in Mindspark by students. The average response time from Mindspark's existing log data, which we calculated, is 22 seconds.
- The Response Rate is the percentage of instances when students answered the question correctly. We calculate the response rate for all questions using the Mindspark's existing log data. We represent the response rate as *RR*. However, we found that *RR* of normal questions are higher than Challenge question hence the *RR* is considered only in Challenge question.
- Frustration instances in the current session are represented by *FrusInst*. The *FrusInst* counts the number of frustration instances detected in the current session.

D. Motivational Messages

The messages created to respond to frustration are discussed in this section. For the first instance of frustration in the current session, the messages are displayed based on the reason for frustration, questions type and the time taken by the student to respond to the question (*Res Time*). The messages created for the first instance of frustration is shown in the Table III.

Based on the reason for frustration, response time and question type, the messages are selected from the table, concatenated and displayed to the students. For example, if the reason for frustration is E3, question type is normal, and $Res\ Time > Average\ response\ time$, then the concatenated messages that is "You did well in the last question and You tried hard to get the correct answer, I am sure you will do well in the next questions". These messages are created to praise the student's effort. The rest of the messages are created to motivate the students.

For the second instance of frustration, the messages are created and displayed based on the question type. The messages created for the second instance of frustration with the condition to display the message is given in Table IV.

These messages are created to attribute the failure to the difficulty of math question and to motivate the student to continue if the question type is a challenge. For normal questions,

TABLE III
MESSAGES TO RESPOND TO FRUSTRATION WITH CONDITION TO DISPLAY THE MESSAGE FOR FRUSTRATION INSTANCE = 1

Condition to Display Message	Message
E2 Challenge	You did well in the last four questions
E3	You did well in the last question
E4	You did well in the last two questions
E5	You did well in the last three questions and got a reward too!
E6	You did well in the last four questions
Res Time > Average response time	You tried hard to get the correct answer
Res Time < Average response time	Try hard
Normal Question	I am sure you will do well in the next questions
Challenge Question	You may solve it next time.

the messages are created to share the student's feelings such show empathy.

For the third instance of frustration, we display the message to receive student's feedback. The message displayed to the student is: "Would you like to give your feedback?". The Mindspark user interface has an option to receive feedback from the students. The message will appear as a speech bubble from an agent—shown in the Fig. 3.

The algorithm to display the messages (step 8) is discussed next.

E. Algorithm to Display Motivational Messages

In this section, we describe the step 8 in Fig. 2 of our approach, that is the algorithm to display motivational messages. For the events listed in Table II, that is for each goal failure, we show the messages based on the student's response time in answering the questions from Mindspark, and question type. We restrict the number of messages per Mindspark session to three. This is to limit the number of interventions to the students during their interaction with Mindspark and avoid students not

TABLE IV
MESSAGES TO RESPOND TO FRUSTRATION WITH CONDITION TO DISPLAY THE MESSAGE FOR FRUSTRATION INSTANCE = 2

Condition to Display Message	Message
Challenge Question	Don't worry, this is a tough question for many of your friends too. You can attempt it again.
Normal question	It is okay to get the wrong answer sometimes. You may have found the question hard, but practice will make it easier. Try again

to focus on feedback messages. The algorithm to display a message based on frustration instance is shown in Algorithm 1.

Algorithm 1. to Display Motivational Messages

```

Require: Res Time, FrusInst, Question Type.
return Message
if FrusInst = 1 & Question Type is Normal then
    Create Message: Based on the reason for frustration and response time, concatenate the messages from Table III and display it to the students.
else if FrusInst = 1 & Question Type is Challenge then
    Create Message: Based on the reason for frustration and response time, concatenate the messages from Table III and display it to the students.
else if FrusInst = 2 & Question Type is Normal then
    Message: It is okay to get the wrong answer sometimes. You may have found the question hard, but practice will make it easier. Try again
else if FrusInst = 2 & Question Type is Challenge then
    Message: Don't worry, this is a tough question for many of your friends too. You can attempt it again.
else if FrusInst = 3 then
    Message: Would you like to give your feedback?
end if
    
```

At the first instance of frustration, the messages from Table III are concatenated and displayed to the students. The

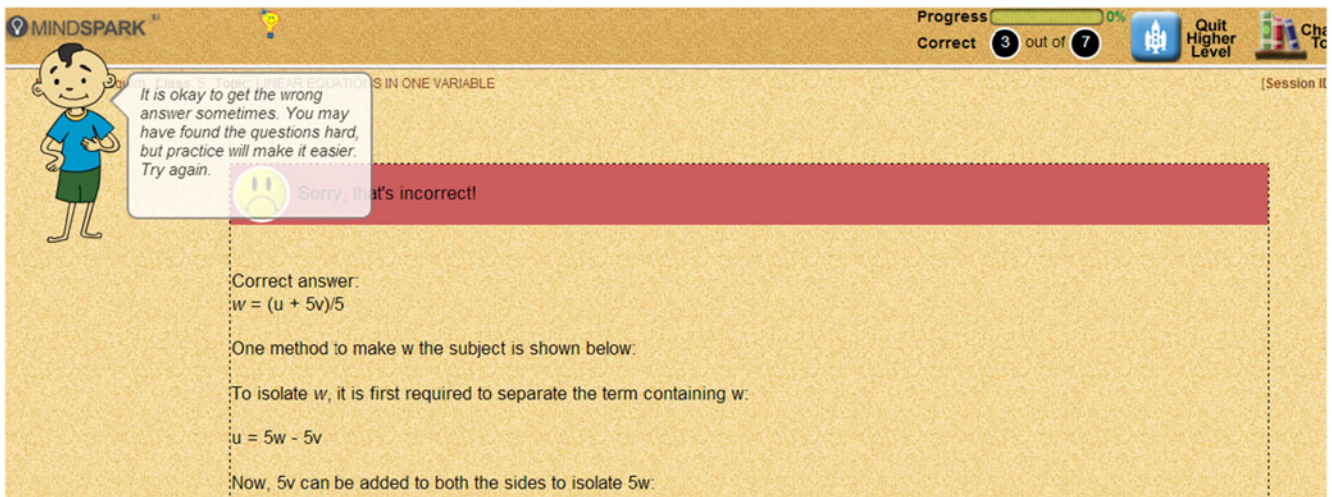


Fig. 3. Screen-shot of mindspark showing a motivational message as speech bubble.

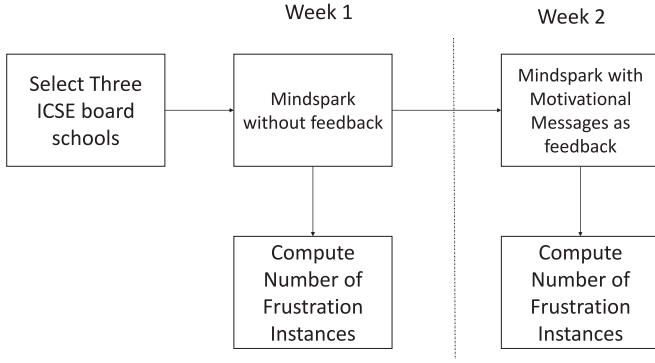


Fig. 4. Methodology to validate our approach to respond to frustration.

condition to display messages for second and third instances of frustration is described in the Algorithm 1. In next section we describe the research design and impact of motivational messages provide to students.

VII. IMPACT OF MOTIVATIONAL MESSAGES

To determine the impact of the motivational messages, we use the within-groups research design (repeated measures) that is comparing the results of our approach to responding to frustration against a control condition. The experimental condition is that students receive motivational messages based on our proposed model and the control condition is that same set of students in the following week receive no feedback messages. We have collected 188 student's Mindspark session data for two weeks for experimental and control condition from three schools and analyzed the impact of responding to frustration using motivational messages. In this section, we discuss our data collection methodology, sample size, analysis techniques and results.

A. Research Design

Our research design that is within-groups analysis is shown in the Fig. 4.

1) *Sample*: We tested the impact of motivational messages on students from three schools that use Mindspark in their curriculum. These schools are from three different cities (Rajkot, Bangalore, Lucknow) in India and follow Indian Certificate of Secondary Education (ICSE²) syllabus. The schools were chosen to represent different cities in India have minimum 100 class 6 students. The theoretical model to detect frustration was developed using data from class six students, hence we collected the data of class six student from three schools. We collected data from 769 class six students, from three schools (326 students in school A, 279 in school B and 164 in school C)

2) *Data Collection Procedure*: The steps to collect data and filtering steps are given below:

- Extract Mindspark session data for one week from class six students in three schools.

TABLE V

DETAILS OF THE DATA COLLECTED FROM THREE SCHOOLS TO MEASURE THE IMPACT OF MOTIVATIONAL MESSAGES ON FRUSTRATION

School	No. of students in Class 6	Mindspark topic in first week without feedback messages	Mindspark topic in second week with feedback messages	Number of Students' data considered for analysis after applying filter criteria
A	326	Integers	Integers	54
B	279	Decimals	Decimals	72
C	164	Algebra	Geometry	62
Total				188

- Remove sessions which have less than ten questions. This is to avoid having a small number of questions in a session.
- Remove those sessions which have less than 11 seconds as an average time spent on each questions. This avoids students who spent less time to answer the question. The 11 seconds cutoff is 50 percent of the average response time computed from the existing log data.
- Retain the unique userIDs and their Mindspark sessions' data.

The selected students' userIDs were stored. In the following week, we implemented our approach to show motivational messages within the Mindspark sessions to the same students. The data collection steps were repeated to select the unique userIDs and their Mindspark sessions' data in the second week. The common unique userIDs across two weeks are retained for the analysis. School A and School B used a same Mindspark topic on both weeks. School C used different Mindspark topic on both weeks.

We collected the Mindspark session data of 188 students' from three schools for two weeks. The details of the data collected from the three schools are shown in Table V.

From the Table V, one can see that the number of students participated in much higher than a number of students considered for analysis. This is due to the filtering criteria we applied, that is removing data of students a) who had session with less than ten questions, and b) session with average time to answer the questions less than 11 seconds. We collected data from 188 students on experimental condition and the same 188 students' data is collected during control condition for analysis.

3) *Data Analysis Technique*: To analyze the impact of frustration, we compare the number of frustration instances in the data of the first and second weeks. We used the trained frustration model from [13] to detect the number of frustration instances in each session. The number of frustration instances in the first week's data of 188 students', without any motivational messages, was calculated. The number of frustration instances in the second week's data of 188 students', with motivational messages to respond to frustration, were also calculated.

B. Results

The number of frustration instances in 188 sessions are visually represented using the box plot in Fig. 5. The figure

²<http://www.cisce.org/>

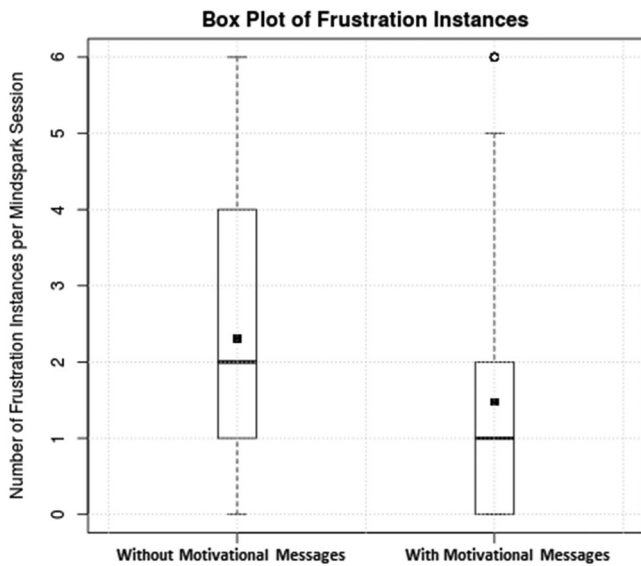


Fig. 5. Box plot of Frustration instances from 188 sessions without and with motivational messages. Box = 25th and 75th percentiles; bars = minimum and maximum values; center line = median; and black dot = mean.

shows the frustration instances without and with motivational messages.

As seen in the box plots, the number of frustration instances after implementing motivational messages is reduced. The circle indicates outliers; this means that the number of frustration instances per session being equal to six is only two after implementing motivational messages to mitigate frustration. The black dots indicate mean of a number of frustration instance in week 1 and week 2. The distribution of frustration instance in both week, doesn't follow the normal distribution and also to avoid the influence of outliers on data representation, we use median as metric to compare the frustration instances and Mann-Whitney U test is used for statistical analysis.

The Mann-Whitney test indicated that the number of frustration instances was greater for control group (Median = 2) than for experimental group (Median = 1), $U = 8869.5$, $p = 0.001$, which rejects the null hypothesis that two distributions are same. The median absolute deviation of frustration instances after implementing motivational messages to avoid frustration is reduced from 2.19 to 1.46. The mean of ranks of frustration instances in sessions without motivational messages is high, compared to the sessions with motivational messages, 212.7 versus 164.3. This indicates that the number of frustration instances is significantly lesser when motivational messages

are shown to the students. For the third instance of frustration in a session, we requested a feedback from the students, however we did not receive any feedback on their frustration.

1) Impact of Responding to Frustration on Individual Schools: To analyze the impact of our approach to responding to frustration on data from individual schools, we analyzed the significant difference in frustration instances for three schools separately, and the results of our analysis are shown in Table VI.

The p-value from the Mann-Whitney test is 0.0136 for school A, for school B is 0.0028 and for school C is 0.0062. Hence, the data from all schools reject the null hypothesis (at the 0.05 level) that two distributions of frustration instances are same. Moreover, the data from Table VI shows that, in all three schools, the number of frustration instances after implementing the approach to avoid frustration is reduced. The math topics used in Mindspark sessions are Integers, Decimals, and Algebra. Significant reduction in frustration instances across different schools and different math topic indicate that the motivational messages to respond to frustration are generalizable to multiple topics in math and across different schools in Mindspark for class six students.

2) Further Analysis: In the previous section, the results indicate that the motivational messages reduced the number of frustration instances in Mindspark sessions. The other possibilities of reduction in number of frustration instances are students' usage of Mindspark in the second week on the same math topic, as in Schools A and B. However, we choose different math topics on week 2 in School C and the results show that number of frustration instance is significantly reduced in week 2 due to feedback. Another reason for the reduction in frustration instances can be attributed to carryover effect in within-subjects research design [29].

To address the carryover effect, we analyzed the data from the schools, which are considered for analysis in this research article, for two weeks without any intervention to their frustration instances. We used the Mann-Whitney test, to check whether there is a significant difference in the number of frustration instances from the Mindspark sessions. The p-value from Mann-Whitney test is 0.45 when there is no treatment to respond to frustration. Since $p > 0.05$, fails to reject the null hypothesis. This analysis indicates that the reduction in frustration instances are not due same math topic being used by students or by research design but due to motivational messages provided as feedback. Overall the results show that the

TABLE VI
IMPACT OF MOTIVATIONAL MESSAGES ON FRUSTRATION IN THREE SCHOOLS

School Code	Number of Sessions	Without Motivational Message		With Motivational Messages		Mann-Whitney's Significance Test
		Sum of Frustration instances	Median	Sum of Frustration instances	Median	
A	54	92	1	57	0	$P < 0.05$
B	72	212	3	148	1	$P < 0.05$
C	62	130	2	72	1	$P < 0.05$

experimental condition with our model led to a statistically significant reduction in the instances of frustration.

VIII. DISCUSSION AND CONCLUSION

In this paper, we have discussed our approach to respond to frustration using motivational messages. The approach we developed for Mindspark was based on addressing students' goal failure. Our approach has been implemented and tested successfully. The results show that motivational messages that use attribution theory and address the reasons for frustration reduced the number of frustration instances per session. The reduction in the number of frustration instances is statistically significant. Motivational messages help the students to reduce frustration and continue with their session, thus enabling them to avoid the negative consequences of frustration.

Our approach can be generalizable to Math topics and class 6 students in schools, in Mindspark. To apply our approach to other systems, the reasons for frustration should be identified while detecting it. Moreover, careful thought is required while creating the messages based on the goal-failure. To generalize our approach to respond to other affective states, the theory-driven approach should be used to detect the affective state, since it enables identification of the reason for the affective state. Subsequently, the reason can be used to respond to the affective state, along lines similar to our approach.

A. Limitation and Future Work

The results of this study indicate that motivational messages reduce the students' frustration instances for class 6 students. However, the motivational message may have a different impact on class 2 or class 3 students, who may not understand the meaning of the messages shown to them or the higher class students might be self-motivated and learned the skills to handle frustration. Thus our approach may be limited to students of the age group with whom the messages were implemented. Going further, in order to generalize our approach to students of different ages, more research is needed on developing motivational messages for different age groups and more studies to test its impact on frustration instances. Second, in our study, we analyzed the impact of motivation messages as a response to frustration, however, a more detailed research study is required to analyze the impact of motivational messages without frustration instances.

Another limitation of this research is the design of the research studies. In this research, we used within-subjects research design for the analysis, which might have lead to carryover effect [29]. In order to address the design limitation, in our future work, we propose to analyze the impacts of motivational feedback messages on number of frustration instances using a dedicated control condition.

In our approach, the reasons for students' frustration instances were used to create the feedback messages and the impact of motivational messages on frustration was analyzed. However, for deeper insight on what factors to be considered while creating the messages, in our future work we propose to analyze the impact of individual motivational messages on students' frustration instances.

Also in our future work, we propose to develop an algorithm to create motivation messages to respond to learner's affective states using, their prior knowledge, type, and duration of the affective state.

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