Live Performance and Emotional Analysis of MathSpring Intelligent Tutor System Students

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Abstract

An important goal of Educational Data Mining is to provide data and visualization about students' state of knowledge and students' affective states. The combination of these provides an understanding of the easiness or hardness of the concepts being taught and the student's comfortability in it. While various studies have been conducted on estimating students' knowledge and affect, little research has been done to transform this collected (Raw) data into meaningful information that is more relatable to teachers, parents and other stakeholders, i.e. Non-Researchers. This research seeks to enhance existing Teacher Tools (An application designed within the MathSpring - An Intelligent Tutoring system) to generate a live dashboard for teachers to use in the classroom, as their students are using MathSpring. The system captures student performance and detects students' facial expressions, which highlight students emotion and engagement, using a deep learning model that detects facial expressions. The live dashboard enables teachers to understand and juxtapose the state of knowledge and corresponding affect of students as they practice math problem solving. This should help teachers understand students' state of mind better, and feed this information back to act and alter their instruction or interaction with each student in a personalized way. We present results of teachers' perceptions of the usefulness of the Live Dashboard, through a qualitative and quantitative survey.

1. Introduction

MathSpring is a personalized intelligent tutoring system that assists 5th-10th grade students in learning mathematics. Students obtain proficiency in different mathematical concepts by practicing various problems and benefiting from several features such as virtual character tutoring, receiving hints and obtaining personalized math problems of the "right" level of challenge. Along with the tutor it also has a Teacher-Tool part which helps teachers to under-

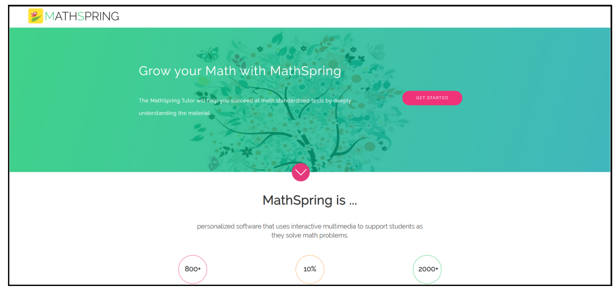

Figure 1. MathSpring Portal

stand and interpret summaries of students' data to help understand students better, and feedback this information to alter their instruction. For instance, general class-wise performance or item-based performance for each class help teachers determine how hard are the students finding the material, where are they lagging behind and so on.

While the students' performance analysis provides teachers great insight, these data are currently being useful in retrospective and batch mode and the teachers could not see the performance of the students live or for students who are currently logged in to the system. Live information about the students would be a great tool to enable teachers give feedback to students while they are working on it. The teachers would also be able to get information about the general as well as specific student's difficulties and the areas where students are finding the difficulty. The current MathSpring system doesn't provide any automatic assessment of the students' affect (mood or emotion) as of now. Understanding any emotion or facial expression change per student would also provide an emotional understanding of the students while they are interacting with the system or solving problems to be precise.

The research is in a pursuit to address the above-mentioned problem by modifying the current design of the MathSpring system, specifically adding more features for the benefit of teachers, who are the users of the Teacher-Tool module. This research includes a new live student dashboard for teachers along with the analysis of the students' performance measurement. We also added a Deep Learning model to predict the facial action units (AU) (11) in an attempt to capture the students' facial expressions. We

Figure 2. Student's view of MathSpring.

have kept the focus on three facial action units, AU4, AU9, and AU12 (eyebrow lowerer, nose wrinkler, and lip corner puller respectively). Since these facial action units bear a positive correlation with their corresponding facial expressions, concerned/stressed, disgust/detestation, happy/good/relaxed respectively, these facial action units seemed a good fit for the predictions and relevance for the teachers.

2. Background Research

Every industry or domain is becoming increasingly data-intensive every day. Data collected, especially involving human subjects are being extensively analyzed and features, behaviours and relationships are being predicted for increased profit or understanding of the subjects. In the field of education, online or computer-based tutoring systems are trending. These systems allow the collection of a large amount of data of the varied students across the globe (e.g ASSISTments (6)).

As per the report released by the US Department of Education on "Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics", education stakeholders are encouraged to use educational data mining and learning analytics to improve student learning. The report suggests for development of a mindset of using more student data strategically (Bienkowski, Feng, Means 2012) (8). The report underlines that student data provides an opportunity to not only learn about them but also to refine the learning content and methodology for the betterment of the way of conveying the teaching material. Thus more and more analytical and visualization tools to enhance teachers' understanding of students should be made available, helping them to make informed decisions and modify their learning instructions to be helpful to students.

Since these data are gathered in real-time, there is a real possibility of continuous improvement via multiple feedback loops that operate at different time scales—immediate to the student for the next problem, daily to the teacher for the next day's teaching, monthly to the principal for judging progress, and annually to the district and state administrators for overall school improvement.

ASSISTments is a tutoring system with a Teacher Dashboard (Heffernan and Heffernan, 2014) (6). Teachers receive feedback on the performance of each student and the class as a whole. With such knowledge, teachers can identify weak students needing additional help and support understanding the concept while also identifying areas where the class as a whole is lagging.

MathSpring.org is also a web-based online tutoring system focusing on helping middle/high school students studying math and preparing for standardized math tests, such as the Massachusetts Comprehensive Assessment System (MCAS). MathSpring is used in public schools in Massachusetts, offering students various features including but not limited to posing questions for students to solve, offering hints, and providing custom feedback to students. Different to ASSISTments, the system is designed to track and capture the cognitive, metacognitive and motivational aspects of a student's state of mind as they progress through the various problems encountered, and personalizes the difficulty of math problems based on an "effort-based tutoring" approach (Arroyo et al., 2014) (1). The "teacher tools" in MathSpring play an important function in this regard. As teachers log in with their usernames and passwords to MathSpring, they can:

1. Set up MathSpring to deliver certain kinds of content (configuration component)

2. Obtain reports about what students have done.

This is especially important because teachers might make decisions (alter their teaching practices) based on this information, creating a loop of information and decisions that feeds back into their teaching and student learning.

However, these data are currently being useful in retrospective and batch mode and the teachers could not see the performance of the students in the in-class mode or who are currently logged in to the system. Also, the system doesn't provide any understanding of the students' affect (mood or emotion) as well in the direct mode.

While learning the students tends to show diverse emotions as shown by D'mello, 2007 (4). Though there has been various ways in which the students' affect has been measured in the past, like interventions to get student's feedback by Wixon et al. (12) and log data model based detection by Corrigan et al. (3). With Deep Learning becoming more and more accessible, the recent focus has been over the computer vision-based models to predict facial expressions, like open-face (2). FERMAT tutor (14), Guru Tutor (9), Whitehill et al. (10) and Gacav et al. (5) are some of the examples which has been experimented and researched on the same line of focus. Although these researches were quite successful in their domain, there is hardly any web-based tutoring system that has been built keeping in my mind the privacy of its users and had tried an end to end analysis and helped in translation of students' emotion and performance analysis and made it available for teachers for their usefulness making it a full cycle from students to teachers.

3. Methodology

The goal of this research is to enhance and enrich the teacher tool module of the MathSpring system to enable the teachers with the live dashboard of the currently logged in users along with the analysis of their performance and predictions over their affects or mood while interacting with the system. In turn, enabling teachers to get more understanding of the current state of the students. This research attempts to seek answers to the following questions:

1. Can we generate live dashboards for teachers that are useful to teachers' teaching, by presenting valuable visualizations about their students' performance?

2. Can we capture the students' facial expressions (by predicting facial action units and confirming samples with the students)?

3. Can we find a correlation between the facial action units and the performance of the students in solving the problems on the system?

4. Can we understand the teachers' responses and estimate the benefits of the enhancement for the teachers?

We have included a new live student dashboard for teachers along with the analysis of the students' performance measurement. We have also added a deep learning model to predict the facial action units (add reference) in an attempt to capture the students' facial expressions. We kept the focus on three facial action units, AU4(eyebrow lowerer), AU9(nose wrinkler), and AU12(lip corner puller). Since these facial action units bear a positive correlation with their corresponding facial expressions, concerned/stressed, disgust/detestation, happy/good/relaxed respectively, these facial action units seemed a good fit for the predictions and relevance for the teachers.

Keeping in mind that the images or video capture of the students are sensitive and private information, we do not save the images or videos of students in any way. Thus, we are also not sending the images or videos over to the servers. To achieve our goal of capturing the facial expressions of the students, we are running our deep learning model over the browser or at the client-side itself using the Tensorflow-JS library. We are only capturing the predictions made by our model only, in our system. Hence preserving the privacy of the students.

To understand the usefulness of the new features we have gathered, analyzed, and presented the teachers' feedback and their views about the changes and their suggestions.

The following sections provide an in-depth understanding of each module and the usability study which had been done to understand the usefulness of the new additions.

4. Facial Expression Predictor

The research includes the development and deployment of facial expression predictor, a deep learning model. The model had been trained and is used for the prediction of the facial action units, mainly AU4(eyebrow lowerer), AU9(nose wrinkler), and AU12(lip corner puller). As said earlier, these facial action units had been chosen as they bear a positive correlation with their corresponding facial expressions, concerned/stressed, disgust/detestation, happy/good/relaxed respectively.

4.1. Dataset

The Extended Cohn-Kanade Dataset (CK+) dataset (7). The dataset consist of posed images of a person along with their corresponding labeled Facial Action Units. The dataset has been used to train our Deep Learning Model which in turn been converted into a Tensorflow-JS model to make it browser deployable.

4.2. Metrics

To evaluate the performance of the deep learning model the following metric has been used:

1. Accuracy,

2. Receiver operating characteristic Area Under Curve score (ROC-AUC score)

4.3. Modelling Pipeline

The pipeline of the model has been developed to build the final model for facial expression prediction. It includes 2 pre-trained specialized CNN models and a new fully-connected neural network model which gives us the final prediction results.

We have described the pipeline in the sequence to clarify the steps involved in the culmination of the final model. The pipeline of the model is depicted in the figure 3.

4.3.1. Face detection

For face detection, a pre-trained SSD (Single Shot Multibox Detector) based on MobileNetV1 has been used. It computes the locations of each face in an image and returns the bounding boxes together with its probability for each face.

Figure 3. Modelling pipeline

Each of the images is run through a face detection algorithm first. On the detection of a face in the image, the face is extracted from the image.

4.3.2. Face landmark detection

A very lightweight and fast, yet accurate pre-trained 68 point face landmark detector. It employs the ideas of depthwise separable convolutions as well as densely connected blocks. The models have been trained on a dataset of 35k face images labeled with 68 face landmark points.

The model is used over the extracted face from passed on by the face detection model to get the facial landmarks (cite here) of the face in the image.

Face detection, face extraction, and facial landmark detection are done using an open-source library face-api.js (14). The library is built on top of Tensorflow.js for face detec-tion/recognition.

4.3.3. Facial Expression Prediction

The final model was created using the Tensorflow Keras library. It is a fully connected neural network that was trained using the features generated using the facial landmarks provided by the previous model.

The input of the model is [24x1] vector containing the attributes corresponding to the facial landmarks of eyebrows, eyes, nose, and mouth. The output contains a [3x1] vector containing the prediction of the confidence of the 3 facial action units.

4.3.4. Model Deployment

We wanted to take the privacy concerns of the students into consideration since we would be dealing with their facial images which would be used while they would be using the MathSpring. To make sure, we trained our model on the publicly available data (7). The training has been done offline using the Tensorflow. Once trained and tested, the model was converted into a Tensorflow JS model.

The Tensorflow JS models are browser friendly and hence is suitable for our research. It enables us to load the model in the browser and make the prediction on the user's physical machine. This plays a significant role in the research as using it we can only send the predictions to be saved at the server-side instead of the images. Hence, resolving the user privacy issue in capturing the images of the students and sending it over to the server for prediction.

We have kept the model in the Amazon S3 bucket which is loaded in the browser at the start of the session of the students on MathSpring. Once loaded, the script starts capturing the images using the webcam of the user's system. The model uses these images for prediction and simultaneously sending the prediction asynchronously to the server.

4.4. Model Results

The result of the final model is as shown below in figure 4.

The model was successful to predict AU12 (lip corner puller or smile) with better accuracy than AU9(Nose wrinkle) and AU4(eyebrow lowerer or frown). The major reason for it was that the training data set had more number of sample of AU12 than those of the A9 and AU4.

AU12(Smile):

Accuracy	0.82
AUC	0.80

AU9(Nose Wrinkle):

Accuracy	0.79
AUC	0.76

AU4(Frown):

Accuracy	0.70
AUC	0.69

Figure 4. Model result

5. User Interface

As part of the research, the new additions were made to the user interface of the MathSpring platform. The new changes have been made both at the student portal as well as in Teachers Tools.

5.1. Student Portal

The student section was enhanced to include:

1. Facial expression prediction:

The interface to the facial expression capturing. The deep learning prediction model is executed at the same time in the browser to generate the prediction values corresponding

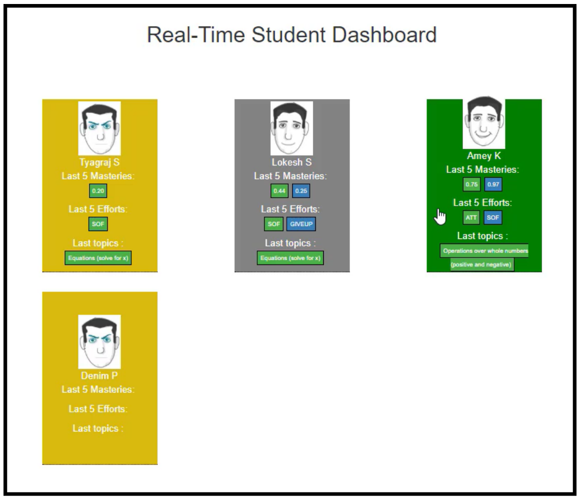

Figure 5. Live Dashboard Page of MathSpring

to the same.

2. Prediction API:

The prediction values generated by the prediction model are saved in the database using a newly created Application Programming Interface(API).

5.2. Teacher Tools

The new addition to the Teacher Tools' user interface are:

1. Live Dashboard

2. Student Detail Page

5.2.1. Live Dashboard

The Teacher Tools has been enhanced with a new live dashboard page. The dashboard depicts the currently logged-in students on the platform. The students are depicted as a rectangular tile on the dashboard page (figure 5).

Each tile of students shows the following information:

a. Image corresponding to student's predicted facial expression

b. Student's name

c. Mastery in the last 5 problems attempted

d. Efforts in the last 5 problems attempted

e. Last topic attempted

The image corresponding to student's predicted facial expression provides teachers a glimpse of how student's facial expression was lately which solving problems on MathSpring.

Mastery is the MathSpring platform's estimation of how much the student has demonstrated to know the topic, ranging from zero to one(0-1). For example, if a student solves 4 problems in a row without mistakes and no help requests, they get a mastery of 0.85 and have mastered the topic. Mastery would increase slower if the student asks for hints, and it would decrease if the student makes mistakes.

Efforts are a way to symbolize the students' efforts, which they have put forward while solving the problems on the MathSpring platform. The platform has described them as 8 states which have been depicted in figure 6.

Effort State	Description of student Behavior
SKIP	The student did nothing and skipped the problem.
NOTR (Not Reading)	The student made a first attempt to solve a problem in a time under 4 seconds –not enough time to even read the problem.
GIVEUP	The student took some action, but then skipped the problem without solving it.
SOF (Solved on First Attempt)	The student solved the problem on their first attempt, without seeing any help.
BOTT (Bottom Out Hint)	The student saw all hints available, including the last available hint that gave the answer.
SHINT (Student Hint Request)	Student answered the math problem eventually right, with at least 1 hint.
ATT (Attempt)	The student didn't see any hints and solved it correctly after 1 wrong attempt.
GUESS	The student solved it correctly with no hints and more than 1 incorrect attempt.

Figure 6. Various effort states and their description

The last topic is the name of the topic of which the student was solving the problems lately.

These information provide teachers a high-level understanding of the student's facial emotions as well as their performance.

5.2.2. Student Detail Page

To get more information about any student, a teacher could click on the corresponding student's tile. This would lead the teacher to the individual student details page which will provide them detailed information about the student (shown in figure 7).

The student detail page contains the following details about the student:

- Facial Action Unit Prediction confidence with time (line chart)
- Facial Action Unit Prediction count comparison (bar chart)
- Student effort distribution (pie chart)
- Mastery in the last 5 problems attempted
- Efforts in the last 5 problems attempted
- Last topics worked on

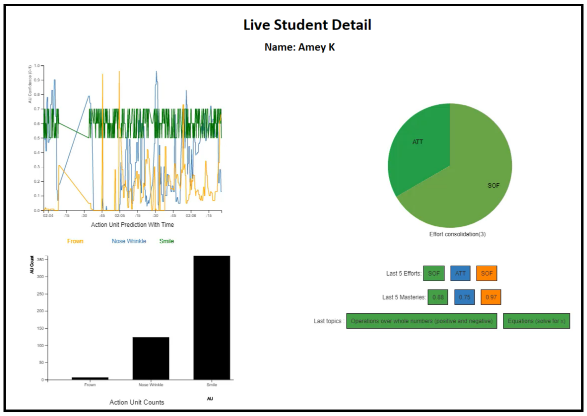

Figure 7. Live student details Page of MathSpring

The facial action unit prediction with time chart provides information about how the strength of the three predicted facial action units or facial expression (Frown, Nose wrinkle, and Smile) is changing over time.

Facial Action Unit Prediction count comparison chart provides the concentration or counts of the three action units(AU4, AU9, and AU12 or facial expression, Frown, Nose wrinkle, and Smile) during the live session of the students.

The student effort pie chart provides the concentration for the different efforts put up by the students on the various math problems attempted by them. It provides an analysis of the students' performance during the session.

Along with it the student detail page also provides the last 5 mastery and efforts depict how the student's performance progress is during the last 5 problems solved. It even provides the teacher with information about the topics which student have been currently working on.

6. Usability Study

To gather the data and provide an in-depth understanding of the new development and changes, we introduced an experiment.

6.1. User Base

The user base for this experiment is college students from Worcester Polytechnic Institute. Although we do want to extend this experiment for other demographics of the students as well. We have selected 7 students for the experiments.

We also selected 4 teachers for the experiment. The teachers were provided with the data collection of the students working on the MathSpring platform.

6.2. Experiment

The experiment includes the students working on the MathSpring platform. While the students are solving the problems, the facial images are run through the deep learning model. The model predicts the facial action units and sends them to the server via the API call. The predictions are saved in the database for further data representation.

Along with the predictions, the platform also captures the performance of the students while solving the problems on the MathSpring.

On the other hand, in teacher tools, when the teacher logs in, they now have the functionality to view the "Live Dashboard" with the currently logged in students. As described earlier, the students are represented as rectangular tiles. The tiles specify high-level facial emotion as well as the performance of the students in solving the problems on MathSpring. The teacher can also view more details about any students on the student detail page by clicking on the student's tile. The student detail page would provide more concrete data representation of the facial emotion data as well as the problem-solving performance of the student.

We have requested feedback from the teachers about their experience on the platform with new development and functionality. We have also analyzed and discussed their viewpoint about the experiment in the next section.

6.3. Method

The methodology to capture the experiment and its presentation for the teachers and stakeholders have been in retrospect manner owing to the unfortunate circumstances.

The method involved the students to log in to the MathSpring platform and solve mathematical problems on it. While they solved problems, the system captured their facial expression with its prediction model.

During the same time, a teacher login was used to capture the view of teacher tools. This was done by capturing the various teacher activities, including, login, navigating to live dashboard, capturing the students' tiles with their specific details, navigating to some of the students' detail page, and capturing their respective information as well.

The video captures the essence of what a teacher might do with the new development undertaken in this research and provide an overall view of the new system development and its use for the teachers.

Later, the teachers have been walked through and details were provided to them about the video and the platform. The teachers had later watched and viewed it with their critical point of view and had provided their views and suggestion as part of the teachers' survey we had devised for

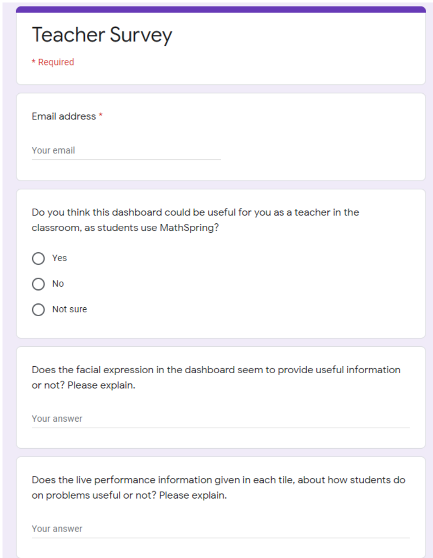
Teacher Survey
* Required
Email address *
Your email
Do you think this dashboard could be useful for you as a teacher in the classroom, as students use MathSpring?
Yes
No
Not sure
Does the facial expression in the dashboard seem to provide useful information or not? Please explain.
Your answer
Does the live performance information given in each tile, about how students do on problems useful or not? Please explain.
Your answer

Figure 8. Survey created for the teachers for feedback.

them.

6.4. Teachers' Survey

The teachers' survey was devised to capture the teachers' response, critical view, and suggestions regarding the new development and its usefulness for teachers.

The survey contains questions which capture teachers' view about various aspect of the research, the impact of it in their understanding students' current state while they solve problems on MathSpring platform (shown in figure 8).

The questions which have been included in the survey are as follows:

1. Do you think this dashboard could be useful for you as a teacher in the classroom, as students use MathSpring?

2. Does the facial expression in the dashboard seem to provide useful information or not? Please explain.

3. Does the live performance information given in each tile, about how students do on problems useful or not? Please explain.

4. Is it valuable to see the facial expression of a student in combination with their problem-solving performance?

5. Is it useful to see information about several students at the same time, organized as tiles?

6. Would you like to see any extra information about students on the tiles that are currently not there? If yes, What would that be?

7. If you can see this as your students use MathSpring, What might you do differently with the information that it provides?

8. When you click on a student, you can see more information. Is this live information about a student meaningful in general?

9. Do you think this detailed live student information be valuable to understand how a student is doing in MathSpring?

10. Would you prefer to see anything else about an individ-ual student's work in this detailed activity per student area?If so, What would that be?

11. What might you do with this detailed information about a student, when managing a full class of students using MathSpring?

We capture the response on a google survey containing the question. We collected the response of teachers over it and have discussed and analyzed them in our next section.

6.5. Usability Study Dataset

To analyze the usefulness and to understand how the usability of the new feature addition for the teachers, we have collected feedback from the teachers using the survey. The data collected using this survey has been studied, analyzed, and presented.

6.6. Result

A qualitative, as well as quantitative analysis of the survey results, had been done to understand the comprehensibility, usefulness, as well as weakness and strength of the newly developed features, were carried out.

The survey results had been by far very encouraging. The teachers have answered most of the questions positively.

6.6.1. Live Dashboard

Teachers have extremely liked the new live dashboard included in the Teachers Tool. Given the history of teachers not being able to monitor the students in live sessions, and the situation of studying from home, the teachers have expressed that the live dashboard seems to be a great way to monitor the classroom. The tile representation of all the live students together in one place is liked by all the teachers.

The new facial expression depiction on the live dashboard has also been considered as a "nice and quick" way of understanding the students' comfort while they are solving the problems. They have also described as a "useful tool" to highlight the students who are feeling not confident while solving the problems and could try and put more focus on them. However, some teachers weren't sure about its use-

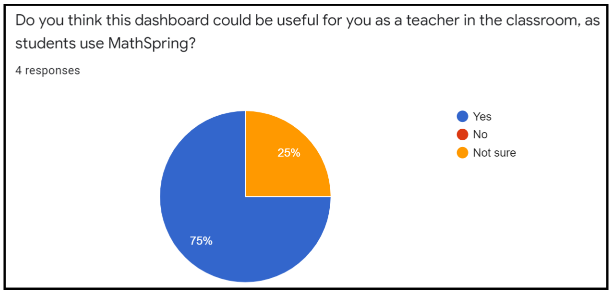

Figure 9. Teachers' response for live dashboard usefulness

fulness to them.

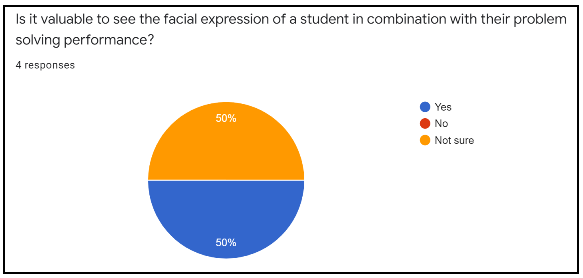

Figure 10. Teachers' response for facial expression's usefulness

The live performance information provided on the student tile has also been considered useful. The teacher has expressed that given the expression and performance measure both, will give them a more pronounced way to understand a student's current status. A teacher also suggested that now they could even quickly try different ways to get the student back on track, if they find him to be less confident or not performing up to the mark and check if it works or not in the live environment.

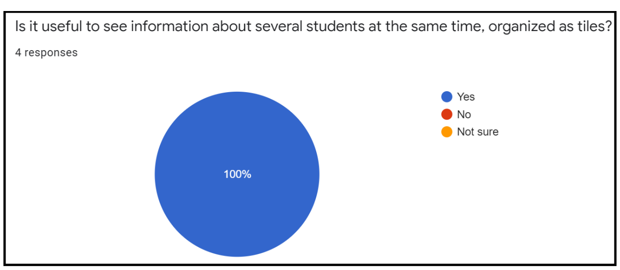

Figure 11. Teachers' response for usefulness of tile representation of students

On being asked about what more would they like to see on the live dashboard, teachers have given a few suggestions. Mainly they would like to see the students' own understanding or assessment of their emotional state. It was an interesting suggestion as it could provide more confirmation to the teachers about the correctness about the expression information provided by the expression predictor.

6.6.2. Student Detail Page

The student detail page was also equally liked by the teachers, as they can try and get more focused information about the individual students. It also gives them more information to personalize their instruction and interaction with each student.

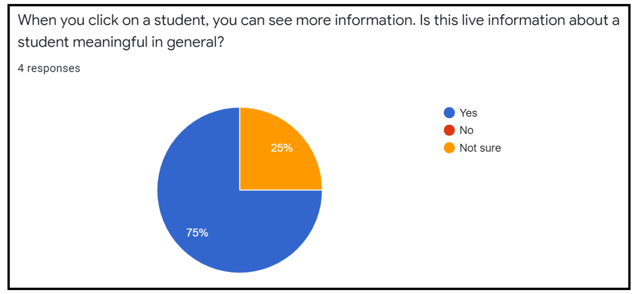

Figure 12. Teachers' response for usefulness of student detail page

Most of the teachers found the information on the student details page as informative and meaningful. Also on being asked about how valuable they think it is on the scale of zero to five(zero being least valuable and 5 being most valuable), they have all responded with three and above(3+).

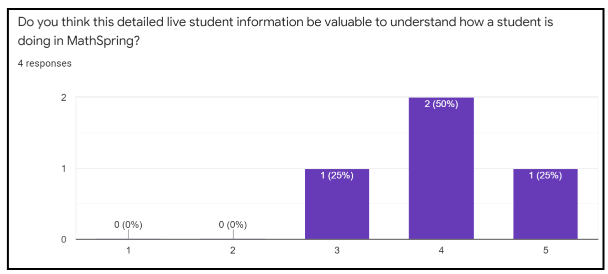

Figure 13. Teachers' response for value of student detail page

As part of the suggestion for more information on the student detail page, teachers wanted to see a bit more specific information about how many wrong answers had been marked by the students out of the total problems attempted by them.

7. Conclusion & Future Work

The usability study had shown promising results. The feedback received from teachers seems to be really encouraging and we believe the new enhancements would tend to help teachers a lot in understanding students and personalizing their response to students as well.

We believe that the work has opened us a direction, the work towards which would promise more help and useful information for teachers in turn to help the students.

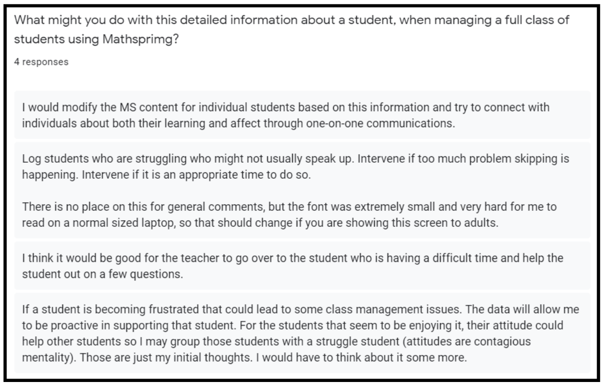

Figure 14. Teachers' response for use of student detail page

The suggestions provided by the teachers in terms of more information and features which they would like to see in the work. We believe that inculcating these changes(more student performance details, students' assessment of their own performance), gathering more data with respect to teachers' responses, and more training data for the refinement of facial expression predictor would provide us better results in the future.

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