

# Reading Students' Multiple Mental States in Conversation from Facial and Heart Rate Cues

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**Abstract:** Students' mental states have been widely acknowledged as crucial components for inferring their learning processes and are closely linked with learning outcomes. Understanding students' complex mental states including concentration, confusion, frustration, and boredom in teacher-student conversation could benefit a human teacher's perceptual and real-time decision-making capability in providing personalized and adaptive support in coaching activities. Many lines of research have explored the automatic measurement of students' mental states in pre-designed human-computer tasks. It still remains a challenge to detect the complex mental states of students in real teacher-student conversation. In this study, we made such an attempt by describing a system for predicting the complex mental states of students from multiple perspectives: facial and physiological (heart rate) cues in real student-teacher conversation scenarios. We developed an advanced multi-sensor-based system and applied it in small-scale meetings to collect students' multimodal conversation data. We demonstrate a multimodal analysis framework. Machine learning models were built by using extracted interpretable proxy features at a fine-grained level to validate their predictive ability regarding students' multiple mental states. Our results provide evidence of the potential value of fusing multimodal data to understand students' multiple mental states in real-world student-teacher conversation.

## 1 INTRODUCTION

There has been increasing attention on students' complex affective and mental states exposed during learning interactions from the educational research community. In the past few years, much research has validated the correlation of students' mental states with measures of their short-term or long-term learning achievements (Craig et al., 2004; Pardos et al., 2014; Rodrigo et al., 2012; Calvo & D'Mello, 2010; Feidakis et al., 2013). Holding a small group meeting composed of teacher-student conversations is one of the most common ways of coaching interactions. (Bell & Cowie, 2001; Shepard, 2005) named this method "assessment conversation," and it is an important link in scaffolding learning. In coaching done in academic small-group meetings, the teacher tends to strike up task-oriented conversations to diagnosis students' learning progress and provide

appropriate intervention by giving comments or problem solution strategies. It is essential for human teachers to be sensitive to changes in the mental states of students order to make real-time decisions on what kind of support to provide and at what times.

(D'Mello & Graesser, 2012) proposed a typical resolution cycle that characterizes dynamic changes in students' mental states, which has been used as a classical, theoretically grounded model in understanding students' complex mental states experienced in learning activities. This dynamic mental-states theory suggests that a student commonly enters interactive learning activities with a state of engaged concentration, and this state will remain until challenges or difficulty emerges, which may result their state transitioning to one of confusion. At this point, the student may transition to one of two paths, go back to being concentrated if they resolve this confusion. Alternatively, the student may transition to frustration at which point, the

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student is unlikely to transition back to confusion or concentration and may be more likely to transition to boredom and then quit learning.

Developing an effective monitoring agent that could sense the occurrence and transition of students' complex mental states, that is, concentration, confusion, frustration, boredom, will be beneficial to helping teachers improve their perceptual and reasoning capabilities and resolve instances of "assistance dilemma" in coaching. An intelligent negative-states-awareness agent could precisely recognize negative mental states in students, especially confused and frustrated ones, infer that students need help catching up with the class, and alert the teacher to direct their coaching resources and aim to help students get out of this learning dilemma.

Much research has used univariate modalities such as video (Grafsgaard et al., 2013), audio (Forbes-Riley & Litman, 2011) and physiological measures (Hussain et al., 2011) to detect affective or mental states in learning activities. Modern sensors have rendered opportunities to support novel methodological approaches to measure students' mental states from multiple perspectives. (Kapoor & Picard, 2005; Whitehill et al., 2011) adopt multimodal approaches for mental state detection that have been explored to improve recognition accuracy.

In this study, a multi-sensor-based data collection system was developed to record students' facial expressions, physiological signals (heart rate), and audio when holding structured conversations with teachers in regular small-group meetings at universities as well as a real-time label annotation tool for collecting the results of observing meeting participants for an evaluation regarding speakers' mental states during conversation. We then propose a multimodal framework for detecting the complex-states of speaker-students, that is, concentration, confusion, frustration, and boredom, by analyzing multimodal features. Machine learning models were also generated to validate the predictive performance of our extracted multimodal features.

## 2 RELATED WORK

Most research regarding emotion recognition in conversation (ERC) has been seen as a Natural Language Process (NLP) task due to the availability of large-scale conversations datasets related to ERC on social media platforms like YouTube, Facebook, Reddit, and Twitter (Poria et al., 2019). Due to the specific character of social media datasets, ERC has been developing into a textual emotion recognition

problem. ERC in educational applications mainly carried out based in human-computer interaction setups, in which researchers analyzed students' mental or affective states when they are interacting with an online tutor system (D'Mello et al., 2006; D'Mello et al., 2008). The few popular available multimodal datasets for mental-state recognition in human-human conversation are based on pre-designed conversation transcripts, such as IEMOCAP (Busso et al., 2008), where actors perform scripted scenarios specifically selected to elicit emotional expressions, and DailyDialog (Li et al., 2017) in which chit-chat data generated in daily life is recorded.

Teacher-student conversation is considered to be a type of task-oriented human-human conversation that is generally carried out around a topic and developed with argumentation logic or through the guidance of a teacher. It is necessary to use teacher-student conversations in real coaching scenarios and explore students' complex mental states from more reliable multiple perspectives, which would provide practical advice for teacher coaching in the real world. Given the validated and precise prediction performance regarding students' mental states done using facial expression or physiological signals, in this paper, we attempted to take advantage of sensory signals including facial and heart rate cues to challenge the task of predicting students' mental states, that is, concentration, confusion, frustration, and boredom in real teacher-student conversation.

### 2.1 Physiological-signal-based Detection

Physiological signals have been commonly used in analyzing mental states because affective or mental states are associated with thoughts and feelings, which are controlled by the autonomic nervous system, and changes in them can be observed by physiological signals such as the heart rate (HR) and brainwaves. (Stevens et al., 2007) used heart rate signals for detecting engage while students interacted with a computer. In our previous work (Peng et al., 2019; Peng et al., 2019), we took advantage of the use of heart rate signals to predict the appropriateness students' answers, and we suggested that students' mental confidence toward correctly giving answers could be indicted by their heart rate features. Several pieces of work (Stevens et al., 2007; Cowley et al., 2013; Luft et al., 2013; Burt & Obradović, 2013) analyzed brainwave EEG signals to understand the cognitive states of students during the learning process.

## 2.2 Facial-signal-based Detection

With the development of computer vision technologies, human mental states have usually been detected on the basis of facial signals extracted from video streams. Among them, eye related features like eye blinking and eye-gaze analysis have been used to help understand students' concentration states (Koning et al., 2010; Gomes et al., 2013). (L. Devillers & L. Vidrascu, 2007) characterize human smiles and laughter by monitoring mouth-noise related features. (Grafsgaard et al., 2013) used mouth features to predict overall levels of concentration, frustration, and learning gain.

## 2.3 Novelty and Contributions

There are several aspects in which this study is different from relevant studies. The contributions we make are (1) instead of students in computer tutor interaction or pre-designed script-based human-human conversation activities, we are interested in an "unplugged" scenario in which a student and his or her advisor teacher have a conversation in real coaching activities. We recorded a 3-month long conversation between students and a teacher held weekly in a face-to-face small-group meeting. In these conversations, students started by stating their research progress, and the teacher initiated the conversation by asking questions to check students' learning situations or look for detailed explanations on uncertain content. Therefore, our research work was applied and validated on a real-world dataset, guaranteeing our results' applicability and practicality in real-world coaching activities. (2) A multi-sensor data collection system was developed and applied in a small group meeting held in a lab, in which we used the iPhone to track the facial information of each meeting participant and used the Apple watch to detect their heart rate signals. Audio of the entire conversation was recorded and transcribed into statements by Google Cloud Speech-to-Text. A real-time mental-state label annotation tool was built and launched for our system, and meeting participants were asked to observe and annotate a speaker's mental states while the speaker was speaking. Our multimodal data collection system could support a 2-3 hours long group meeting composed of conversation activities held amongst multiple participants. Participants' facial data, physiological data, heart rate, audio, and the context of the conversation as well as a speaker's mental states labels are synchronized, captured, and stored structurally, and this shows the potential utility of our

system for long-term multimodal dataset collection as well as for supporting the analysis of real-world teacher-student conversation; (3) With few exceptions, most existing work relies on univariate modality, while our study attempts to propose a multimodal framework based on multiple data streams, that is, facial and heart rate signals used for predicting students' complex mental states: concentration, confusion, frustration, and boredom. A series of aggregated level features were extracted and discussed as facial and physiological patterns in characterizing students' mental states in conversation. We generated several machine learning predictive models to validate the precognitive ability of our proposed multimodal framework and achieved good results.

## 3 MULTIMODAL CONVERSATION DATA COLLECTION

### 3.1 Participants

The participants were 4 undergraduate/graduate students and their advisor professor, and they ranged in age from 21 to 24 years. The professor has been guiding these 4 students for 1 to 2 years by holding regular small-group progress report meetings every week. Data for our multimodal dataset was collected on the basis of these 4 students when they had a conversation with the professor, in which they reported their weekly study progress in a small-group meeting held in a lab.

### 3.2 Data Collection System and Procedure

In these conversation-based small group meetings, students sat in a circle as shown in Fig. 1.



Figure 1: Conversation-based small group meeting.

Before the meeting, as shown in Fig. 2, all participants were asked to start a face tracking function developed for the iPhone XR, which was placed on the desk in front of each of them, by choosing their name and pressing the recording button. A paired Apple Watch worn on their wrist was started synchronously to detect their heart rate.

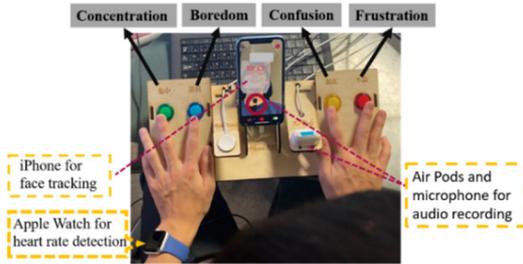


Figure 2: Multi-sensors for multimodal data collection.

An AirPods earphone and a microphone on the chest were also worn in order to collect the audio data when they had a conversation with the teacher.

Students reported their research progress while displaying content related in the form of a presentation, and the whole meeting was segmented into four presentation chunks according to the first and last presentation slides for each student detected by our system as shown in Fig. 3. For each chunk, there would be continuous conversation between the presenting student and teacher in which the teacher started by asking questions regarding the content being presented and the student answered them.

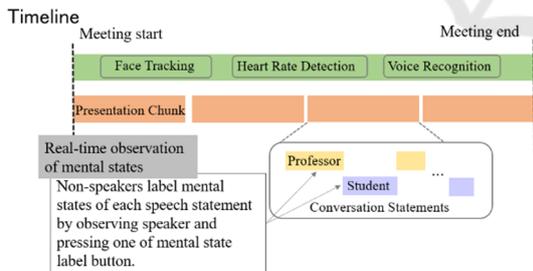


Figure 3: Structured meeting content.

A real-time label annotation tool was designed to collect a speaker's mental state annotations within the

speech of the conversation. Label annotation could be generally categorized into self-reporting or observation by a third party. Self-reporting method carried out with student answering survey questioners or watching video after experiments, and recalling their mental states occurred in experiment (O'Brien & Toms, 2010, D'Mello & Mills, 2014). Other streams of work rely on external human observation and annotation (Parsons & Taylor, 2012), in which teachers or peers observe students' mental states on site or off site and evaluate their mental states.

Since we aimed to collect real-time mental state labels without interrupting the speaker, we made mental-state label buttons placed with the other sensors on the desk. As shown in Fig. 2, there are four buttons representing four mental states from left to right: concentration, boredom, confusion, and frustration. We adopt third party observation method in which we asked all of the non-speakers (for each presentation chunk, conversation only occurs between the presenting student and teacher, so the other non-presenting students and the listener in conversation are non-speakers) to observe a speaker's mental states during his or her speech and press one of the buttons to record the start time for observing the mental states and press the same button again when they observed the end or transition of the state.

Using our multimodal data collection system, we recorded and generated structured meeting minutes including a multimodal dataset of the participants comprised of facial and heart rate data taken during the whole meeting. Fig. 3 presents our structured meeting content as well as rich conversation data including audio and text information transcribed by Google Transcribe, speaker information, and mental state labels within the speech of the conversation.

We collected a total of 11 small-group meetings for a total of 1320 minutes with a mean length of 330 minutes of multimodal data per student including video of their face and their heart rate during the whole meeting. For a single meeting, each student had a mean of 25-30 minutes per presentation chunk including research progress statements and conversations with teacher, with the longest continues conversation lasting 17 minutes and the shortest only about 7.2 minutes. Audio and transcript information for each conversation were also recorded.

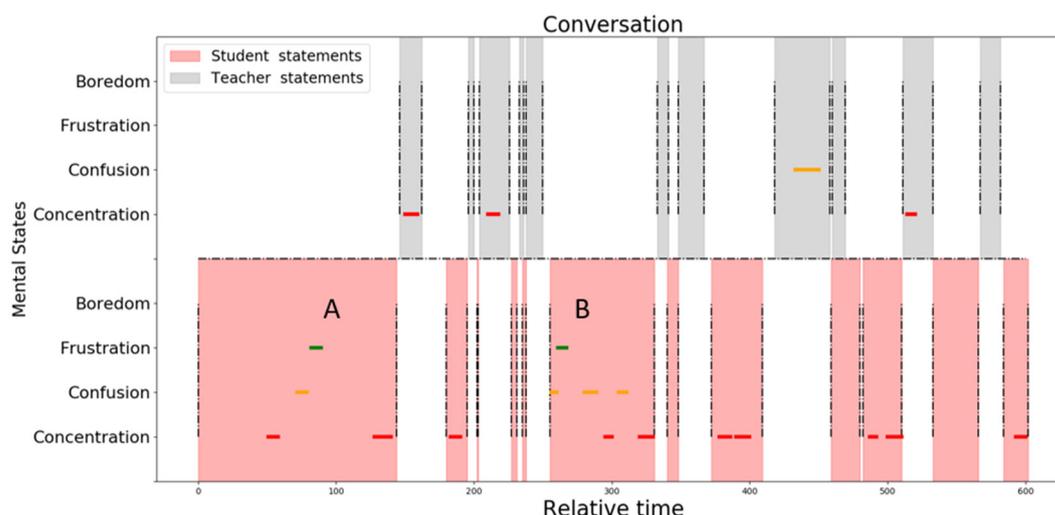


Figure 4: Example of annotated mental states within continues teacher-student conversation. Area with pink is students’ speech, while grey area is teacher’s speech, which is segmented by start and end time along meeting timeline using dotted line. Horizontal lines inside each speech chunk represent annotated mental states at this speech clip annotated by one non-speaker. State transition paths: (A) concentrated, confused, frustrated, and back to concentrated; (B) confused, frustrated, confused, concentrated, confused, and back to concentrated.

## 4 METHODOLOGY FOR PREDICTING MULTIPLE MENTAL STATES

### 4.1 Qualitative Analysis on Mental State Annotation

All non-speakers were asked to annotate speaker’s mental states during speech by pressing one of the labeled buttons and to press the same button again when the conclusion or transition of the state was observed. As shown in Fig. 4, we give an example of annotated mental states within a continuous teacher-student conversation. From the information shown in the figure, (1) annotations mainly occurred for longer speech. (2) As shown in (A), there is a clear transition shift from concentration, confusion, frustration, and back to concentration. (B) The speaker’s mental state started from confused and transited to frustrated and then back to confused and then to concentrated. These two paths support the students’ dynamic mental-state change theory we introduced at the beginning of this paper, which guarantees the analyzability of our experimental dataset. (3) There were fewer annotations within the teacher’s speech, which may indicate that the teacher intended to show sparse mental state changes or their mental states were not clear enough to be observed.

There were two types of annotators: participant-student and the teacher, who was also a participant of the conversation. We adopted Cohen’s Kappa (Landis & Koch, 1977) to measure the inter-rater agreement of the two different annotators. If the kappa varies from 0.41 to 0.6, the agreement level is considered to be moderate, and if it falls within the range of 0.6–0.8, the issue is considered to be in substantive agreement between different subjective opinions. If the kappa is in the range 0.81–0.99, the two participants can be considered to have almost reached perfect agreement. We randomly selected 60 speech clips (at least 10 sec apart) annotated by the teacher and two graduate school students, and we computed the Kappa value between teacher and student A, teacher and Student B, and student A and student B for each mental state annotation. The results are shown in Table 1.

Table 1: Inter-rater agreement (Cohen’s Kappa) of mental state annotation between teacher and student.

	Teacher vs Student A	Teacher vs Student B	Student A vs Student B
Concentration	0.60	0.57	0.59
Confusion	0.58	0.61	0.53
Frustration	0.42	0.42	0.33
Boredom	0.35	0.39	0.37

As seen in Table 1, the inter-rater agreement value for concentration, confusion, and frustration were relatively higher than boredom for all annotator

groups. This is perhaps because, in teacher-student conversations, students do not easily show that they are bored. Due to the higher inter-rater agreement level between teacher and student B, we selected the first frame of the annotation and the next 150 frames (5 seconds) as one mental state predictive segment.

## 4.2 Quantitative Analysis

### 4.2.1 Facial Feature Analysis

We implemented face tracking on the iPhone by employing ARKit packages (ARKit, 2017), which utilizes depth sensor data to generate a single facial mesh over a user's face and detects various information of the user's face, including its position, orientation, and a series of blend shape coefficients to represent a corresponding value of specific facial features recognized by ARKit. The blend shape coefficient is a floating-point number indicating the current position of the respective feature relative to its neutral configuration, ranging from 0.0 (neutral) to 1.0 (maximum movement). Fig. 5 shows an example using the feature to characterize the eye blinking of the right eye by measuring the closure of the eyelid.

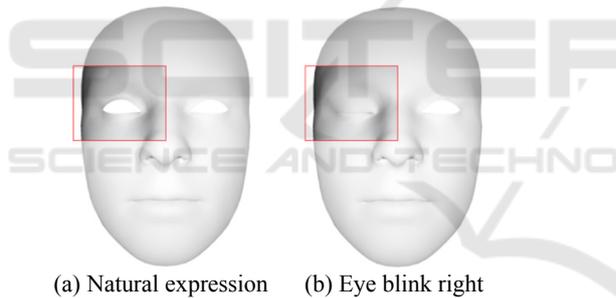


Figure 5: (a) Natural expression with coefficient = 0.0, (b) maximum movement of right eye blinking with coefficient = 1.0 (eyeBlinkRight, 2017).

We extracted a series of facial features describing the movement patterns of eyes and mouth at an average frequency of 30 Hz. The first 300 (10 seconds) from each conversation were used as a baseline for computing the features.

**Eye-related Features:** Eye blink action has always been used in predicting mental states, and we used the eyeBlinkLeft and eyeBlinkRight coefficients for describing the closure of the eyelids over the left and right eyes. The Pearson  $r$  score was computed to measure the correlation coefficients between the two eyes and was 0.995, which indicates consistency between the movements of the two eye, and we calculated the average of eyeBlinkLeft and eyeBlinkRight coefficient values to characterize eye-

blink patterns. A Savitzky-Colay filter was applied with a filtering window size of 15 frames to remove spike artefacts within the eyeBlink time series data. Eye blink rates were calculated through peak detection.

We measured several features relative to the eyes as patterns for describing relative eye movement, including eyeBlink action frequency, the proportion of time a student had their eyes closed during blinking (closure time), the proportion of time the students' eyes were open, and the amplitude value of eyeBlink. **Mouth-related Features:** To characterize the 2D movement of the mouth, we employed the mouthOpen/Close coefficients to characterize mouth movement along the vertical direction with mouthSmileLeft and mouthSmileRight coefficients which measure the upward movement of both corner of the mouth, together with mouthFrownLeft and mouthFrownRight coefficients which measure downward movement of both corner of the mouth to describe the mouth corner movement within four quadrants. We took the average of mouthSmileRight and mouthFrownRight to compute the movement of right corner of the mouth and the average of mouthSmileLeft and mouthFrownLeft for the left corner movement. We also took the mean value of mouthOpen and Close to compute the lip movement.

As shown in Fig. 6, we give an intuitive example of one student's mouth actions during conversation using the features we introduced above: (a) mouth open, (b) mouth closed, (c) smile (both corners of mouth shows clear upward movement), and (d) mouth frown (both corners clear downward movement).

We then computed the velocity, acceleration of the lips and both mouth corners, and the proportion of time students spent smiling and frowning.

### 4.2.2 Heart Rate Feature Analysis

The heart rate data we collected was at a frequency of 1 Hz. We computed the time domain features including the mean, standard deviation (std.), root mean square successive difference (RMSSD), max, min, variance, and the heart rate trend by calculating the difference between two adjacent heart rate points. If the number of positive differences was more than the negative one, we assumed that this heart rate period showed an upward trend; if not, it showed a downward one. We also computed spectral entropy as frequency domain features. In Table 2, we summarize the features derived from facial and heart rate signals.

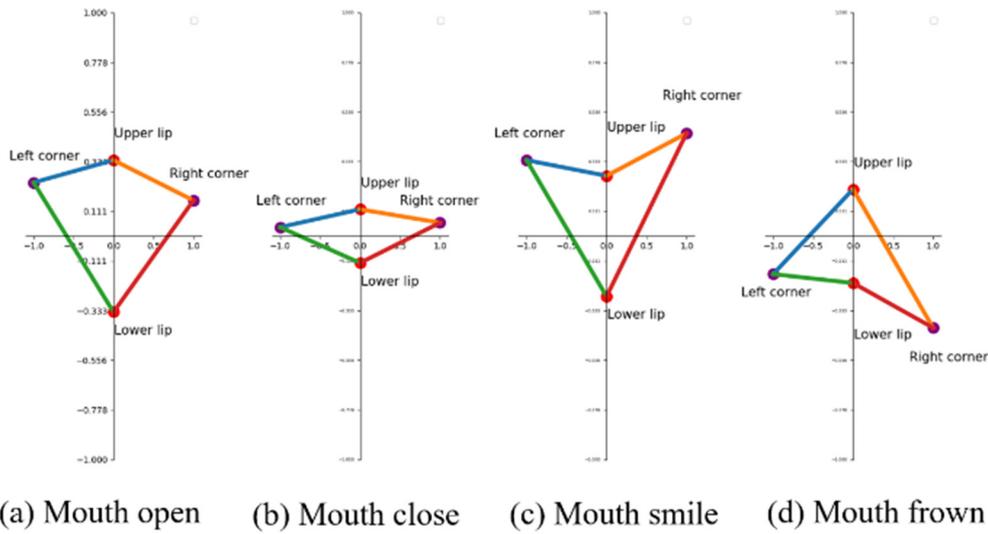


Figure 6: Visualization of mouth actions using mouth related features.

Table 2: Summary of features.

	Feature descriptions	
Eye-related features	Eye blink frequency	
	Proportion of time closed	
	Proportion of time open	
	Mean, Std., Max, Min, range of eye blink amplitude	
Mouth-related features	Lips & mouth corner	Mean, Std., Max, Min, range of velocity
		Mean, Std., Max, Min, range of acceleration
	Proportion of “smile” time	
	Proportion of “frown” time	
Heart rate-related features	Mean, Std. Max, Min, RMSSD, HR trend	

### 4.3 Predicting Multiple Mental States

In this section, we evaluate the predictive utility of a combination of feature sets derived from the facial signals and heart rate signals in predicting the students’ mental states in conversation. We adopted Softmax Regression (SR), Multilayer Perceptron Neural Network (MLP), and Random Forest (RF) machine learning methods to build multi-class classifiers for each combination of feature sets and a leave-conversation block-out method to evaluate the predictive performance for each multi-class classifier.

We started from the baseline model by using the raw facial features, mouth and eye related raw signals, and we then used the aggregated level facial related features summarized in Table 2. We finally estimated the performance for a complete set features fusing multiple modalities by adding raw HR data to raw

facial features and adding aggregated statistic HR features to aggregated facial features. In Table 3, we report the macro F1-scores for each classifier.

Table 3: Summary of macro F1-score for each classifier for different feature sets.

	Raw facial	Aggregated facial	Raw facial and HR	Aggregated facial and HR
SR	0.54	0.59	0.51	0.59
MLP	0.64	0.64	0.67	0.63
RF	0.59	0.63	0.62	0.68

From the results shown in Table 3, for raw facial features, we achieved an F1-score of 0.64 for the MLP model and 0.59 for the RF model, which indicates that MLP can better learn interpretable features from facial raw signals as proxies for the task of predicting mental states than random forest. Our proposed aggregated facial features improved the predictive ability from 0.59 to 0.63 for RF model, while they did not provide additional information for the MLP model, which maintained the same F1-score. Raw HR added additional utility over the raw facial features, with F1-scores that increased from 0.64 to 0.67 for MLP and from 0.59 to 0.62 for the RF model. Moreover, the aggregated HR features helped the aggregated facial features improve the predictive ability for the RF model but decreased the ability for the MLP model. These results show that our proposed feature extraction method could provide a more interpretable description of students’ different mental states than as traditional machine learning model, that

is, random forest. Finally, the SR model showed an overall lower predictive ability than the other two models. We think that this may indicate the non-linear relationship between these two modalities, which is valuable to validate in the future.

## 5 CONCLUSION AND FUTURE WORK

In this paper, we aimed to predict students' complex mental states, that is, concentration, confusion, frustration, and boredom in real-world student-teacher conversation from a multimodal data stream that included facial and heart rate signals. A multi-sensor-based multimodal data collection system was developed and applied in a real group meeting in a lab, where task-oriented conversation activities occurred between 4 graduated students and their teacher. We recorded 11 group meetings to create a dataset for over 1320 minutes of multimodal data on the basis of facial and heart rate signals as well as the audio and textual information of the conversation. A real-time mental state annotation tool was designed. We asked all non-speakers in the meeting to annotate mental state labels for speakers while they made a presentation. The inter-rater agreement for each annotated mental state class between the teacher and student was measured, and we used a teacher and one student who had a higher consistency level in terms of annotation for the mental-state annotation results.

We then proposed a multimodal framework for exploring interpretable multimodal patterns in predicting students' mental states in conversation. Several visual features were extracted for characterizing eye and mouth movements including eye blink frequency, the proportion of time for which eyes are closed or open, the mean, std., max, min, and range of eye blink amplitude. We measured the movement of the lip and mouth corners vertically and in four quadrants, along with the proportion of time for "mouth smile" and "mouth frown." We also took advantage of heart rate data as our physiological proxy for mental state prediction.

Last, we generated several machine learning models including Softmax Regression (SR), Multilayer Perceptron Neural Network (MLP), and Random Forest (RF) using different multimodal feature sets. Our proposed multimodal features (aggregated facial and heart rate features) achieved the best predictive ability regarding students' mental states when using the random forest model. These results validated our proposed multimodal framework.

The framework could provide fine-grained interpretable features as a proxy in predicting students' complex mental states in conversation and also illustrated the utility of fusing information from multiple modalities in this prediction task. In addition, MLP performed well in automatically learning features from raw facial and heart rate signals, which may provide evidence for potential possibilities of predicting students' real-time mental states.

There are multiple types of future work that could be considered for our scalable multimodal dataset and the current prospective experiment's results. (1) The teacher (conversation partner)'s multimodal data were also collected, which we are going to take a deep dive and analyze the potential utility of interaction behavior patterns in predicting presenter-students' mental states. (2) In addition to facial and heart rate signals, audio and textual information from the conversation were also collected. We plan to extend our multimodal framework by adding the conversation data to improve our prediction ability. (3) In terms of application, we are going to launch our mental-state prediction model for use with our data collection system. We aim to alert teachers when students are facing an "assistance dilemma" shown through their confusion and frustration, in order to let teachers provide a timely and suitable intervention to improve students' learning outcomes.

## REFERENCES

- Apple Inc., Arkit — Apple developer documentation, <https://developer.apple.com/documentation/arkit>, Accessed: 2017-12-04
- Busso, C., Bulut, M., Lee, C.-C., Kazemzadeh, A. Mower, E., Kim, S., Chang, J. N., Lee, S., & Narayanan, S. S. (2008). IEMOCAP: Interactive emotional dyadic motion capture database, In: *Language Resources and Evaluation*, 42(4), 335.
- Bell, B. & Cowie, B. (2001). The characteristics of formative assessment in science education. In: *Science Education*, 85(5), 536-553.
- Burt, K. B. & Obradović, J. (2013). The construct of psychophysiological reactivity: Statistical and psychometric issues. In: *Developmental Review*, 33(1), 29-57.
- Craig, S., Graesser, A., Sullins, J., & Gholson, B. (2004). Affect and learning: an exploratory look into the role of affect in learning with AutoTutor. In: *Journal of Educational Media*, 29(3), 241-250.
- Calvo, R. A. & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. In: *IEEE Transactions on Affective Computing*, 1(1), 18-37.

- Cowley, B., Ravaja, N. & Heikura, T. (2013). Cardiovascular physiology predicts learning effects in a serious game activity. In: *Computers & Education*, 60(1), 299–309.
- D’Mello, S. K., Craig, S. D., Sullins, J., & Graesser, A. C. (2006). Predicting affective states expressed through an emote-aloud procedure from AutoTutor’s mixed-initiative dialogue. In: *International Journal of Artificial Intelligence in Education*, 16(1), 3-28.
- Devillers, L. & Vidrascu, L. (2007). Real-life emotion recognition in speech. In: *Speaker Classification II*. pp. 34–42. Springer, Berlin, Heidelberg.
- D’Mello, S. K., Craig, S. D., Witherspoon, A., Mcdaniel, B., & Graesser, A. (2008). Automatic detection of learner’s affect from conversational cues. In: *User Modeling and User-adapted interaction*, 18(1-2), 45-80.
- D’Mello, S. & Graesser, A. (2012). Dynamics of affective states during complex learning. In: *Learning and Instruction*, 22(2), 145–157.
- D’Mello, S. (2013). A selective meta-analysis on the relative incidence of discrete affective states during learning with technology. In: *Journal of Educational Psychology*, 105(4), 1082.
- D’Mello, S. & Mills, C. (2014). Emotions while writing about emotional and non-emotional topics. In: *Motivation and Emotion*, 38(1), 140-156.
- EyeBlinkRight, Apple developer documentation, [https://developer.apple.com/documentation/arkit/arfaca\\_nchor/blendshapelocation/2928262-eyeblickright](https://developer.apple.com/documentation/arkit/arfaca_nchor/blendshapelocation/2928262-eyeblickright).
- Forbes-Riley, K. & Litman, D. (2011, June). When does disengagement correlate with learning in spoken dialog computer tutoring? In: *International Conference on Artificial Intelligence in Education*. pp. 81–89. Springer, Berlin, Heidelberg.
- Feidakis, M., Daradomis, T., & Caballé, S. (2013, January). Building emotion-aware features in computer supported collaborative learning (CSCL) systems. In: *Alpine Rendez-Vous (ARV) Workshop on Tools and Technologies for Emotion Awareness in Computer-Mediated Collaboration and Learning (ARV 2013)*.
- Gomes, J., Yassine, M., Worsley, M., & Blikstein, P. (2013, July). Analysing engineering expertise of high school students using eye tracking and multimodal learning analytics. In: *Educational Data Mining*.
- Grafsgaard, J. F., Wiggins, J. B., Boyer, K. E., Wiebe, E. N., & Lester, J. C. (2013, July). Embodied affect in tutorial dialogue: student gesture and posture. In: *International Conference on Artificial Intelligence in Education*. pp. 1–10. Springer, Berlin, Heidelberg.
- Grafsgaard, J., Wiggins, J. B., Boyer, K. E., Wiebe, E. N., & Lester, J. (2013, July). Automatically recognizing facial expression: Predicting engagement and frustration. In: *Educational Data Mining*.
- Hussain, M. S., AlZoubi, O., Calvo, R. A., & D’Mello, S. K. (2011, June). Affect detection from multichannel physiology during learning sessions with AutoTutor. In: *International Conference on Artificial Intelligence in Education*. pp. 131–138. Springer, Berlin, Heidelberg.
- Kapoor, A. & Picard, R. W. (2005). Multimodal affect recognition in learning environments, In: *Proceedings of the 13th Annual ACM International Conference on Multimedia*, pp. 677–682.
- Koning, B. B. de, Tabbers, H. K., Rikers, R. M., & Paas, F. (2010). Attention guidance in learning from a complex animation: Seeing is understanding?, In: *Learning and Instruction*, 20(2), 111–122.
- Landis, J. R. & Koch, G. G. (1977). The measurement of observer agreement for categorical data. In: *Biometrics*, 159-174.
- Li, Y., Su, H., Shen, X., Li, W., Cao, Z., & Niu, S. (2017). DailyDialog: A manually labelled multi-turn dialogue dataset. In: *arXiv preprint arXiv*: pp. 1710-03957.
- Luft, C. D., Nolte, G., & Bhattacharya, J. (2013). High-learners present larger mid-frontal theta power and connectivity in response to incorrect performance feedback. In: *The Journal of Neuroscience*, 33(5), 2029–2038.
- O’Brien, H. L. & Toms, E. G. (2010). The development and evaluation of a survey to measure user engagement. In: *Journal of the American Society for Information Science and Technology*, 61(1), 50-69.
- Pardos, Z. A., Baker, R. S., San Pedro, M. O., Gowda, S. M., & Gowda, S. M. (2014). Affective states and state tests: Investigating how affect and engagement during the school year predict end-of-year learning outcomes. In: *Journal of Learning Analytics*, 1(1), 107-128.
- Parsons, J. & Taylor, L. (2012). Student engagement: What do we know and what should we do? In: *University of Alberta*.
- Poria, S., Majumder, N., Mihalcea, R., & Hovy, E. (2019). Emotion recognition in conversation: Research challenges, datasets, and recent advances. In: *IEEE Access*, 7, 100943-100953.
- Peng, S., Ohira, S., Nagao, K. (2019). Prediction of Students’ Answer Relevance in Discussion Based on their Heart-Rate Data, In: *International Journal of Innovation and Research in Educational Sciences (IJRES)*, 6(3), 414-424.
- Peng, S., Ohira, S., Nagao, K. (2019). Automatic Evaluation of Students’ Discussion Skills Based on their Heart Rate. In: *Computer Supported Education*, 1022, 572-585, Springer.
- Rodrigo, M. M. T., Baker, R. S., Agapito, J., Nabos, J., Repalam, M. C., Reyes, S. S., & San Pedro, M. O. C. (2012). The effects of an interactive software agent on student affective dynamics while using; an intelligent tutoring system. In: *IEEE Transactions on Affective Computing*, 3(2), 224-236.
- Shepard, L. A. (2005). Linking formative assessment to scaffolding. In: *Educational Leadership*, 63(3), 66-70.
- Stevens, R. H., Galloway, T., & Berka, C. (2007, July). EEG-related changes in cognitive workload, engagement and distraction as students acquire problem solving skills. In: *International Conference on User Modeling*. pp. 187–196. Springer, Berlin, Heidelberg.
- Whitehill, J., Serpell, Z., Foster, A., Lin, Y. C., Pearson, B., Bartlett, M., & Movellan, J. (2011, June). Towards an optimal affect-sensitive instructional system of cognitive skills. In: *CVPR 2011 Workshops*. pp. 20–25. IEEE.