Automatic Evaluation of Presenters' Discussion Performance based on Their Heart Rate

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Abstract: Heart rate (HR) variability (HRV) has recently seen a surge in interest regarding the evaluation of cognitive performance as it always be used to measure the autonomic nervous system function. In this study, we argue that a presenters' HR data can be used to effectively evaluate their cognitive performance, specifically presenters' performance of discussion which consists of several Q&A segments (question and answer pairs) compared with using traditional natural language processing (NLP) such as semantic analysis. To confirm this, we used a non-invasive device, i.e., Apple Watch, to collect real-time updated HR data of presenters during discussions in our lab-seminar environment, their HR data were analyzed based on Q&A segments, and three machine-learning models were generated for evaluation: logistic regression, support vector machine, and random forest. We also discuss the meaningful HR and HRV features (metrics). Comparative experiments were conducted involving semantic data of Q&A statements alone and a combination of HR and semantic data. The HR data of presenters resulted in effective evaluation of discussion performance compared with using only semantic data. The combination of these two types of data could improve the discussion performance evaluation ability to some extent.

1 INTRODUCTION

Discussion is often considered as an effective active learning process in academia, and is usually conducted in the form of presenters organizing and explaining their current research through the presentation session and participants involving peers and instructors who raising questions to challenge and point out problems in presenters' research and the presenters answering them to facilitate knowledge discovery and exchange. We call question and answer pairs Q&A segments. Considering the specific process of discussion and its significant influence on students' active learning process, we are thinking about finding a way to effectively evaluate their discussion performance to improve their active learning ability and help them carry out future research activities. Taking full advantage of discussion data, such as audio-and-video, facial expression, semantic information, etc. can help us evaluate presenters' discussion performance. The "discussion-mining (DM)" system (Nagao et al., 2004) can provide us analyzable discussion data, which we previously developed, it generates multimedia meeting minutes of lab discussions containing audio-visual and semantic information of Q&A segments given by participants and answered by the discussion presenters. Given the crucial importance of questions asked by the participants, if the presenter can give answers that are close to the correct answers, in other words give high-quality answers, it means that the presenter has a high understanding skill of the questions and a strong communication skill, which represents a high discussion performance. Therefore, many higher-quality answers given by presenters indicates better discussion performance. We decided to evaluate presenters' answer-quality of Q&A segments and as a method of evaluating their discussion performance.

Natural language processing (NLP) has often been used as the main method to evaluate the answer quality of Q&A segments, Patil and Lee (Patil and Lee, 2016) analyzed certain linguistic features to identify expert answers. Some previous studies described using contextual features, such as n-gram, to predict the answer quality of Yahoo! Answers (Agichtein et al., 2008) or computed text-based features such as if there are yes-like words in the answers statements (Belinkov et al., 2015). However, the personal characteristics of speakers or recorders

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inevitably decrease the generalization performance of the answer-quality evaluation of Q&A segments.

Considering that the discussion process is a type of cognitive activity, which could result in changes in certain physiological data, such as heart rate (HR) variability (HRV), several studies have proven that HR is an important index of the autonomic nervous system regulation of the cardiovascular system (Camm et al., 1996) (Anderson, 1995) (Acharya et al., 2006). Therefore, there has been increasing focus on observing the correlation between HR data and cognitive activities. A study on measuring the HR during three cognitive tasks (Luque-Casado et al., 2013) has revealed the affection of cognitive processing on HRV. The stress level also has been assessed during Trier Social Stress Test tasks, a type of cognitive activity, by using HR and HRV metrics (Pereira et al., 2017). Judging from the large amount of evidence presented, we argue that HR data of presenters can be used to effectively evaluate the answer-quality of Q&A segments, which is helpful in improving presenters' discussion performance compared with a traditional semantic analysis method.

In this paper, our starting point is categorizing the answer-quality of Q&A segments of discussions into low quality and high quality according to how correctly a presenter answered participants' questions. Our first goal was to collect presenters' heart rates (HRs) during their discussions based on our DM system in real time. The second goal was to conduct an experimental investigation to prove that the HR of presenters can be used to effectively evaluate the answer-quality of Q&A segments.

We first introduce our lab-seminar DM system we used to generate our experimental Q&A segment data. We then explain our HR-data acquisition system. Next we introduce the three types of binary classification machine-learning methods we used as evaluation models: logistic regression (LR), support vector machine (SVM), and random forest (RF), as well as the HRV features (metrics), and discuss the evaluation results. Finally, we explain our comparative experiments with the purpose of comparing evaluation performance by using Q&A statements' semantic data alone and a combination of these two types of data.

2 DISCUSSION-MINING SYSTEM

Seminar-style meetings that are regularly held at university laboratories are places where exchanges of opinions on research content occur. Many comments on future work are included in their meeting records. However, as discussions at meetings are generally not recorded in detail, it is difficult to use these for discovering useful knowledge. Our laboratory developed and uses a DM system that records the content of face-to-face meetings while providing metadata (Nagao et al., 2004). Looking back on the challenges presented in remarks is essential for setting new goals in activities, but their existence may be buried in many other remarks in the minutes.

In our laboratory at Nagoya University, we have used this DM system to record detailed meetings in the laboratory for over ten years. This system enables all participants to cooperate to create and use structured minutes. This system is not fully automated, i.e., the secretary manually writes the contents of the speech, and each speaker tags his/her speech. Therefore, we can generate data with high accuracy.

The meeting style supported by the DM system is that the presenter explains a topic while displaying slides, and Q&A with the meeting participants is either conducted during or at the end of the presentation.

Specifically, using multiple cameras and microphones installed in a discussion room, as shown in Figure 1, and a presenter/secretary tool we created, we record the discussion content. In the center of the discussion room, there is also a main screen that displays the presentation materials and demonstration videos, and on both sides, there are sub-screens for displaying information on and images of the participants who are currently speaking.

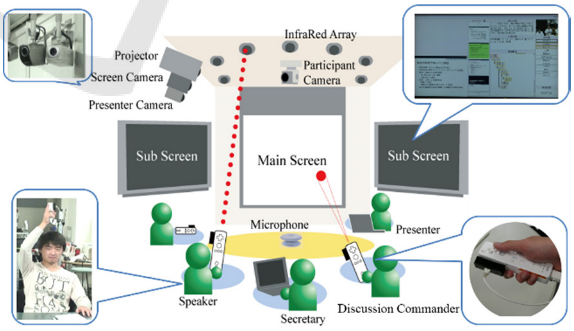


Figure 1: Overview of discussion-mining (DM) system.

The DM system records slide presentations and Q&A sessions including participants while segmenting them in time. As a result, content (discussion content), as shown in Figure 2, is recorded and generated.

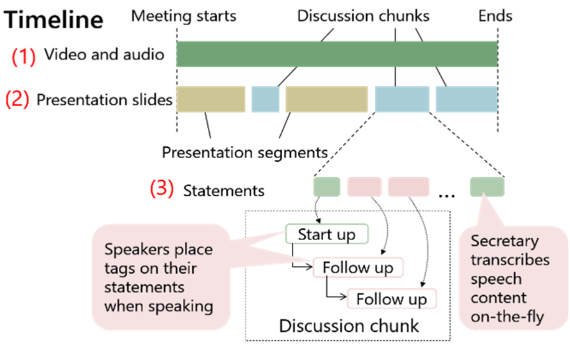


Figure 2: Overview of discussion content.

Every participant inputs metadata about his/her speech using a dedicated device that is called a discussion commander, as shown in the lower right of Figure 1. Participants who specifically ask questions or make comments on new topics assign start-up tags to their statements. Also, if they want to speak in more detail on topics related to the immediately preceding statement, they provide a follow-up tag. Furthermore, the system records pointer designates the location/time for the slide and information on the button for or against the statement during the presentation and during the Q&A session. Marking information on important statements is also recorded.

We also developed a system for searching and viewing recorded data. In this discussion-content-browsing system, a user can search the contents of the agenda from the date and participant information, view past discussions similar to the ongoing debate, and effectively visualize the state of the discussion, as shown in Figure 3.

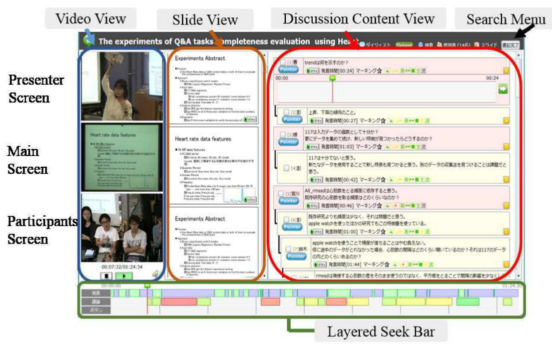


Figure 3: Discussion browser of DM system.

The discussion view presents the semantic structures of discussion content, which records all the questions given by the participants and corresponding answers given by the presenter, which we call Q&A segments, as shown in Figure 4.

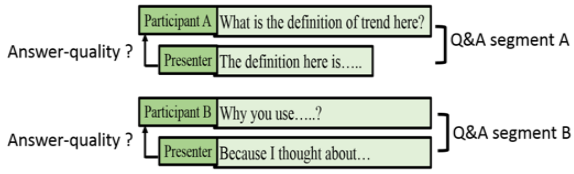


Figure 4: Q&A segments in discussion.

3 PRESENTERS' HEART-RATE DATA ACQUISITION

Smart watches, such as Apple Watch, Fitbit series, and Microsoft Bands, contain wearable sensors to accurately detect users' biological data, such as HR and blood pressure. Such non-invasive detection makes it possible to link users' biological information with their daily activities. Iakovakis and Hadjileontiadis (Iakovakis and Hadjileontiadis, 2016) used Microsoft Band 2 to acquire HR data of users to predict their body postures. In our study, we used Apple Watch to collect presenters' HR data based on our DM system and visualize their HR data during discussions.

3.1 Heart-Rate Data Acquisition

Through the Health Kit framework on Apple Watch, which we asked presenters to wear on their left hand during discussions, as showed in Figure 5, presenters' HR data were acquired almost in real time in 5-7 sec intervals. The collected HR and presenters' information is displayed on the Apple Watch screen as well as synchronously presented on the HR browser.

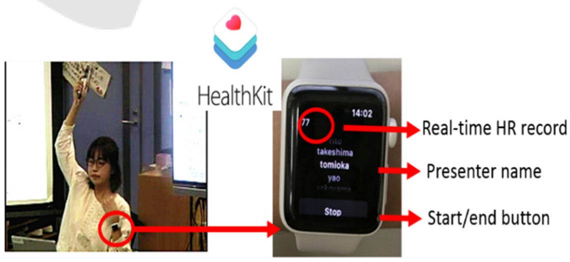


Figure 5: Presenters' heart-rate (HR) acquisition.

3.2 Heart-Rate Browser

As Figure 6 shows, the HR information displayed on the browser consists of three parts: a search menu to survey the historical HR information, an HRV graph, and HR records that enable users to understand the HRV information in detail.

Search Menu: The historical HR data and user information can be searched through this search menu at the top of the browser.

HR Graph: The graph provides an intuitive way to observe presenters' HR data changes throughout the discussion.

HR Records: The HR data at each point of the discussion with which the presenter's information can be checked.

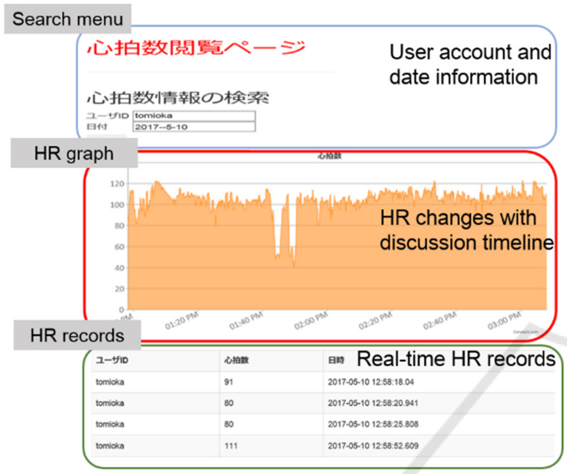


Figure 6: HR browser.

4 EVALUATION EXPERIMENTS BASED ON PRESENTERS' HEART RATE

To automatically evaluate discussion performance, we started from analyzing the answer-quality of Q&A segments, which are the most important constituent components generated around the discussion topic. Our goal was to validate our argument that HR of discussion presenters can be used to effectively evaluate the answer-quality of Q&A segments during discussions. We will describe our heart rate data analysis process in subsection 4.1 and then introduce our evaluation experiments in subsection 4.2.

4.1 Heart-Rate Data Analysis

All HR information of presenters during their discussions is displayed in a graph, as shown in Figure 7 (a), which presents the presenter's complete HR detected per minute throughout the discussion. The HR segments in each Q&A segment was then extracted and displayed in a graph, as shown in Figure 7 (b), which shows the HR data during the answer period (blue line) and answer period (orange line). We then computed 18 HR and HRV features from all Q&A segments as well as the question and answer periods separately.

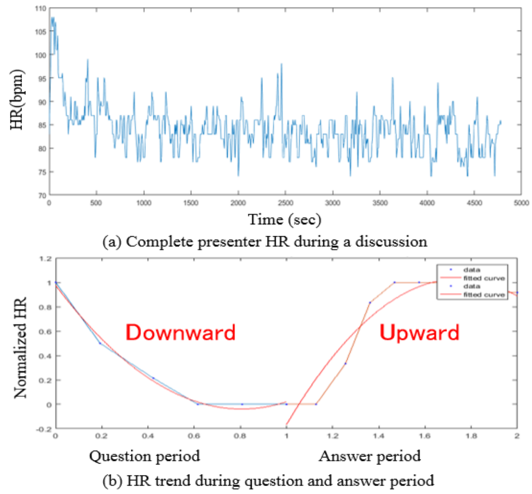


Figure 7: HR graphs.

The HR and HRV features include mean, standard deviation (std.), and root mean square successive difference (RMSSD) from these three periods, which has been proven as an important metric for understanding HRV differences under cognitive activities (Wang et al., 2009) and (De Rivecourt et al., 2008). The trends in the HR of these three periods were also computed by calculating the difference between two adjacent HR points. If the number of positive differences was more than the negative one, we assumed this HR period shows an upward trend, if not, this HR period shows a downward trend, as shown in the Figure 7 (b). We used a quadratic curve (red line) to more clearly present the HR trend for readers. We can see that HR during the question period shows a downward trend and an upward trend during answer period.

Table 1: HR and HRV features.

HR period	HR and HRV features
Both periods	mean, std., RMSSD, trend,
	Freq. all mean, Freq. all std.
Question period	mean, std., RMSSD, trend,
	Freq. question mean,
	Freq. question std.
Answer period	mean, std., RMSSD, trend,
	Freq. answer mean,
	Freq. answer std.

We also divided the HR data of these three periods into the following nine ranges: less than 60 bpm, 60–70 bpm, 71-80 bpm, 81-90 bpm, 91-100 bpm, 101-110 bpm, 111-120 bpm, 121-130 bpm and more than 130 bpm. The mean and std. were calculated to describe the HR appearance-frequency distribution in each range. Table 1 summarizes these 18 features

4.2 Evaluation Experiments based on Presenters' Heart Rate

4.2.1 Experimental Data

We collected discussion data from 9 presenters from 9 lab-seminar discussions in 4 months, and 12 undergraduate and graduate students and 3 professors made up the participants, the discussions were carried out following the presenters' research contents report with the participants asking questions related to the discussion topic then answered by the presenters. There were 117 complete Q&A segments extracted from these 9 discussions, and the answer-quality of these Q&A segments were evaluated by the corresponding participants who asked the questions by gave a score based on a five-point scale; 1 = very poor, 2= poor, 3= acceptable, 4= good, 5 = very good. We obtained 66 high-quality answers with scores from 4–5, and 51 low-quality answers with scores from 1–3.

4.2.2 Evaluation Models

We adopted three evaluation models: LR, SVM, and RF, to carry out binary classification of the Q&A segments' answer quality. About 80% of Q&A segments were randomly selected as the training data set and the remaining 20% as the test data set.

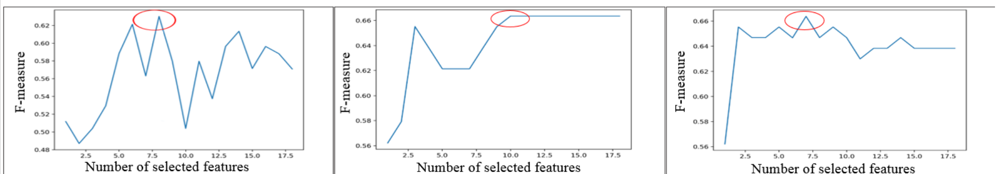
4.2.3 HR and HRV Feature Selection

Considering that using all the features we computed, as discussed in Section 4.1, may decrease the performance of the evaluation models, we used recursive features elimination (RFE) (Guyon et al., 2002), which ranks the features according their importance to the different evaluation models. To determine the best size of the feature subset, we used the RFE with 5-fold cross-validation (RFECV) method. By calculating the F-measure (or F1 score that is the harmonic mean of precision and recall), we extracted the best performing feature subset that could achieve the best evaluation performance for the corresponding models.

Figure 8 shows three sub-graphs that separately illustrate the best subset of all the HR and HRV features for each model at the top and the feature-importance-ranking results at the bottom. The highest F-measure was obtained when seven or eight key features were included in the subsets for the LR model; therefore, the first seven or eight features surrounded by the red rectangle were considered as two candidate feature subsets for the LR model. Similarly, the first ten features comprised the candidate subset for the SVM model, and there were two candidate feature subsets for the RF model which involved seven or eight features in the ranking list counted from the top.

4.2.4 Results

For the LR model, we obtained a 0.79 F-measure by using the eight-feature candidate subset and an



(a.1) Feature subset with f-measure

(b.1) Feature subset with f-measure

(c.1) Feature subset with f-measure

Ranking	Feature name	Ranking	Feature name
1	Ans_trend	10	Que_mean
2	Freq_ans_std.	11	Freq_que_std.
3	All_mean	12	Freq_que_mean
4	All_rMSSD	13	Ans_mean
5	Ans_std.	14	Freq_all_std.
6	All_trend	15	Que_std.
7	Que_trend	16	All_std.
8	Freq_all_mean	17	Que_rMSSD
9	Ans_rMSSD	18	Freq_ans_mean

(a.2) Feature importance ranking

(a) LR model

Ranking	Feature name	Ranking	Feature name
1	All_mean	10	Freq_ans_mean
2	Ans_trend	11	All_std.
3	All_rMSSD	12	Que_mean
4	Freq_ans_std.	13	Freq_all_mean
5	Ans_std.	14	Que_std.
6	Freq_que_std.	15	Que_rMSSD
7	Que_trend	16	Ans_mean
8	Freq_que_mean	17	Freq_all_std.
9	All_trend	18	Ans_rMSSD

(b.2) Feature importance ranking

(b) SVM model

Ranking	Feature name	Ranking	Feature name
1	Que_mean	10	Que_std.
2	All_rMSSD	11	All_std.
3	Que_trend	12	Que_rMSSD
4	Ans_std.	13	Ans_mean
5	Freq_ans_std.	14	Freq_que_std.
6	All_trend	15	Freq_all_mean
7	All_mean	16	Freq_que_mean
8	Ans_trend	17	Ans_rMSSD
9	Freq_ans_mean	18	Freq_all_std.

(c.2) Feature importance ranking

(c) RF model

Figure 8: HR and HRV feature selection for each evaluation model.

F-measure of 0.74 when using the seven-feature candidate subset; therefore, we used the eight-feature subset to train our LR model. We obtained an measure of 0.8053 for the SVM model with the ten HR and HRV features we selected in advance. For the RF model, when there were 36 trees and 19 terminal nodes on each tree we obtained the highest F-measure of 0.87. In this case, we chose an eight-feature subset. Table 2 lists the evaluation results for each model.

Comparing the F-measures of each model, the RF model exhibited superior evaluation performance compared with the LR and SVM models. By considering all three models, the HRV data of presenters showed an outstanding evaluation performance of Q&A segments' answer quality. Meanwhile, we focused on the following seven HRV features: All mean, Answer trend, All RMSSD, Freq answer std., Answer std., Question trend, and All trend, which exhibited the largest effect on all three models.

Table 2: Evaluation results of each model.

Evaluation model	F-measure
LR	0.79
SVM	0.8053
RF	0.87

5 COMPARATIVE EXPERIMENTS

As discussed in the previous section, we experimentally found that the discussion presenters' HRV features can be used to effectively evaluate Q&A segments' answer quality and as a discussion-performance evaluation method. In this section, we discuss determining whether the HRV features of discussion presenters exhibit better discrimination performance regarding the evaluation of Q&A segments' answer quality than traditional semantic features extracted from presenter statements. We conducted two comparative experiments by generating LR, SVM, RF models based on the semantic features of Q&A statements alone and a combination of these two types of data.

5.1 Comparative Experiments based on Semantic Analysis

5.1.1 Semantic Features

To find meaningful semantic characteristics as semantic features for evaluating the answer-quality of Q&A segments, we conducted a statistical analysis on 1246 Q&A segments from discussions we recorded before in our lab environment and also manually evaluated their quality by gave a score based on a five-point scale in advance. From these survey samples, we obtained 993 high-quality Q&A segments and 253 low-quality segments.

A morpheme bigram was constructed based on these survey Q&A segments by using MeCab, which is a fast and customizable morphological analyzer for Japanese (downloadable from the Web at https://sourceforge.net/projects/mecab/), calculated the occurrence frequency of all bigrams, and extracted several bigrams if their occurrences were much higher than 0.15%. We selected 14 morpheme bigrams as the semantic features for evaluating Q&A segments' answer quality.

5.1.2 Results

As shown in the second column of Table 3, The RF model exhibited the strongest discrimination ability than the other models, even though we only used the semantic features that received an F-measure of 0.583.

Table 3 also compares the evaluation performance of HRV and semantic features. We can clearly see that presenters' HR and HRV features brought out excellent discrimination ability regarding Q&A segments' answer quality compared with semantic features in all evaluation models. These results provide favourable evidence regarding our original argument that using presenters' HR and HRV features can effectively evaluate the answer-quality of Q&A segments in discussions.

Table 3: Comparison of evaluation performance of HR and semantic features for each evaluation.

Evaluation model	F-measure	
	Semantic features	HR features
LR	0.5	0.79
SVM	0.54	0.8053
RF	0.583	0.87

5.2 Comparative Experiments based on Combination of HR and Sematic Data

In the previous section, we proved that HR data of presenters can be more effective regarding Q&A segments' answer-quality evaluation than traditional semantic features from presenter statements. We also discovered seven meaningful HR and HRV features having a larger effect on each evaluation model.

To maximize the evaluation performance regarding Q&A segments' answer quality, we combined HR data and semantic data. We decided to combine the seven most meaningful HR and HRV features with the semantic features extracted previously. Three new LR, SVM, and RF models were constructed based on the same training dataset, and the same test dataset was also used to evaluate the evaluation performance, Table 4 shows the performance comparison of all three models.

Table 4: Evaluation-performance comparison of HR and semantic features and their combination for each evaluation model.

Evaluation model	F-measure		
	HR features	Semantic features	Combination of HR and semantic features
LR	0.79	0.5	0.79
SVM	0.8053	0.54	0.833
RF	0.87	0.583	0.916

As the results indicate in Table 4, combining the HR data of presenters and semantic data of Q&A statements clearly increased evaluation ability than using each type of data alone. The SVM and RF models obtained a 3 and 4% increase in F-measure, respectively, but there was no obvious increase for the LR model.

6 CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this study, we argued to take advantage of presenters' HR data to effectively evaluate the answer-quality of Q&A segments in their discussions. We developed a heart-rate acquisition system based on our DM system with the help of presenters wearing a non-invasive device, i.e., Apple Watch. The collected HR data were presented on a HR browser.

To verify our argument, we generated three binary classification models for evaluation: LR, SVM, and RF, and selected the seven most meaningful features out of all 18 HR and HRV features: All mean, Answer trend, All RMSSD, Freq answer std., Answer std., Question trend, and All trend, which had the largest effect on all three models. We obtained an F-measure of 0.79 for the LR model, 0.8053 for the SVM model, and 0.87 for the RF model. These results indicate that HR data of presenters can be used to evaluate the answer-quality of Q&A segments of discussions. To further verify our argument, we conducted a comparative experiment in which we extracted semantic features from Q&A statements from past survey data and used the same method to construct and evaluate three different evaluation models. The comparative results revealed that HR data of presenters can exhibit more effective evaluation on the answer-quality of Q&A segments than semantic data, providing convincing evidence to support our argument.

After recognizing the excellent performance of HR data on evaluating Q&A segments' answer quality, we focused on whether the combination of two types of data can achieve more effective evaluation performance. We used the seven most meaningful HR and HRV features of presenters and semantic features together to evaluate answer-quality. There was an obvious increase in evaluation performance for the SVM and RF models; F-measure reached 0.9 of the RF model.

As we discussed in the introduction section, discussion activity forms an active learning process in which presenters explain their current research through the presentation session and receive questions from participants about their research content during the question-and-answer session. These questions are useful for helping presenters troubleshoot problems that have not been resolved or are ignored at the present stage. Many higher-quality answers given by presenters indicates a better understanding of participants' questions and higher-degree mastering of their research content, as well as stronger communication skills, which are all criteria for a high level of discussion performance.

In this study, we have shown that presenters' HR data can effectively evaluate the answer-quality of Q&A segments and as a method of automatic evaluation of presenters' discussion performance compared with using traditional NLP such as semantic analysis. And our finding that the accuracy of evaluation can be improved by combining traditional semantic data with presenters' physiological data HR offers experimental evidence for using multi-modal data to effectively evaluate students' cognitive performance.

6.2 Future Work

We will focus on the application of our argument suggested in this paper to facilitate students' discussion performance. We plan to develop a follow-up function in which feedback regarding low-quality Q&A segments is given to presenters after discussions to encourage them to spend more time on re-understanding the questions, to sort out their research to find more accurate answers, and to strengthen the communication skills to give participants a more understandable description, in the long run, to effectively improve students' discussion performance.

As another future plan. After we recognizing the excellent performance of users' physical data such as HR in evaluating cognitive activities, we intend to use this result as a theoretical basis, and take advantage of multimodal data especially users' physical data like blood pressure, pulse data with the heart rate, as well as the traditional discussion data such as audio-and-video data recorded by our DM system. We plan on using deep learning methods as we believe the amount of data that we may add in the future will increase and we desire improved accuracy.

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