Transdisciplinarity and the Future of Engineering
B.R. Moser et al. (Eds.)

doi:10.3233/ATDE220697

Mental States and Cognitive Performance Monitoring for User-Centered e-Learning System: A Case Study

Ziqing XIA[a], Cherng En LEE[a], Chun-Hsien CHEN[a], Jo-Yu KUO[b,1], and Kendrik Yan Hong LIM[a]
[a] *School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore 639798, Singapore*
[b] *Department of Industrial Design, National Taipei University of Technology, Taipei City, 10608 Taiwan*

Abstract. The unprecedented long-term online learning caused by COVID-19 has increased stress symptoms among students. The e-learning system reduces communications between teachers and students, making it difficult to observe student's mental issues and learning performance. This study aims to develop a non-intrusive method that can simultaneously monitor stress states and cognitive performance of student in the scenario of online education. Forty-three participants were recruited to perform a computer-based reading task under stressful and non-stressful conditions, and their eye-movement data were recorded. A tree ensemble machine learning model, named LightGBM (Light Gradient Boosting Machine), was utilized to predict stress states and reading performance of students with an accuracy of 0.825 and 0.793, respectively. An interpretable model, SHAP (SHapley Additive exPlanation), was used to identify the most important eye-movement indicators and their effects on stress and reading performance. The proposed model can serve as a foundation for further development of user-centred services in e-learning system.

Keywords. Stress, cognitive performance, online education, user-centered design

Introduction

Stress occurs amongst many students and can result from different forms of pressure. Psychosocial stress, a common type of stress, is caused by situations under social threats and these situations often involve varying level of social evaluation as well as achievement expectations. This stress can arise from the fear of failure for tests and attaining poor grades, which may be resulting from high social expectations to perform well academically. Such sensitivity towards social evaluation can result in intense stress, leading to social exclusion and a series of negative health impacts [1]. Cognitive performance, also known as cognitive functioning, is a measure of an individual's mental abilities, comprising of learning, problem solving and decision making [2]. Chronic stress has effects on one's cognitive performance in both short and long term [3]. It can result in cognitive decline, and this decline includes reduction in attentional focus

[1] Corresponding Author, Mail: jyk@ntut.edu.tw.

required for information processing [4]. Prolonged exposure to high levels of stress can also impact decision-making abilities negatively, resulting in cognitive impairments [5].

The COVID-19 pandemic has posed an unprecedented crisis in the education domain, leading to a worldwide transition from face-to-face teaching mode to online education mode [6]. The new remote learning pattern reduces the communication between teachers and students, making students feel isolated and unsupported with respect to their studies, and thus becomes an important source of stress for students [7]. Teachers also have indicated the difficulties of motivating students and assessing their learning performance in the remote teaching context [8]. As a result, teachers may not be able to provide in-time guidance and intervention for those students who have learning difficulties or suffer from academic stress [9]. This may result in escalation to severe levels of stress in students. Therefore, it is of great importance to equip the e-learning platforms with the capability to monitor the stress states and learning performance of students. The successful recognition of individuals' states is the foundation for further development of user-centred services and promotion of student well-being.

The eye-tracking technique can acquire eye-movement data that is important to an on-going cognitive task in a non-obtrusive and real-time fashion, which is a suitable tool for monitoring mental states and cognitive process in the e-learning context. Past research done thus far has utilised simple eye movement features to identify cognitive responses or behavioural changes upon stress induction [10-12]. Eye tracking had proven to be feasible in evaluating real-time physiological and psychosocial changes via a non-invasive manner. This study will focus on evaluating the effectiveness in prediction of stress and cognitive performance of students using eye-movement data. It will also advance beyond previous research by evaluating how eye tracking features can predict patterns in cognitive performance such as information search and decision-making when in stressed environment. In the context of engineering education, the study enhances e-learning activites and can be extended to specialized engineering theoretical courses from technical operations to safety and regulations for retraining and induction purposes. Furthermore, this study will look into the inclusion of more complex eye movement features to further analyse the correlation of these patterns with the use of supervised machine learning algorithms.

1. Related work

In this section, previous studies involving the use of eye-tracking data for prediction purposes will be reviewed. Recent studies have utilized the gaze and pupil features to identify indicators of stress amongst students. Pupil diameter was found to increase when stress and cognitive load increase [13, 14]. Further research done went on to explore the utilization of other eye-tracking features involving fixation and saccadic parameters. Herten et al. [10] studied the relation and behavior of one's fixation under stress induction. Even though there might not be any direct causal effect between fixation and memory performance, participants were observed to fixate longer on subjects relating to stressful situations. Sanchez et al. [15] supports these findings with their study on individuals with Major Depressive Disorder as it was found that these individuals also tend to fixate and engage longer on the negative stimuli when placed in stressed situations.

There were also other studies that were done to investigate the relationship between decision-making and stress using eye-tracking methods. In a study that utilized the Iowa

Gambling Task (IGT) to examine how stress affects decision-making in risky situations, participants spent more time inspecting disadvantageous decks when stress is induced [16]. On the other hand, Stankovic et al. [17] studied the information processing of cockpit warning displays when in emergencies. Eye-tracking data were used to assess the individual's decision-making abilities when experiencing acute stress. In this case, participants were found to have less fixations and spent less time fixating on images in the Matching Familiar Figures Task (MFFT).

Besides stress-related studies, there are many other eye-tracking research that assess one's cognitive abilities or performance. Yang et al. [18] explored the possibility of utilizing eye-tracking methodology to predict cognitive structures and information processing modes of students. When going through controversial reports, students tend to focus more on processing inference information, as indicated by more and longer fixations, so that it aids them in developing their cognitive structures to better analyze the reports. In another study [12], eye tracking was used to analyze cognitive impairment in patients that are suffering from neurological disorders. A common finding was that most of these patients demonstrated shorter fixation and a higher number of saccades when discovered to be in cognitive deficit. Borys and Plechawska-Wójcik [19] investigate the visual attention differences between participants of different cognitive performance levels in a neuropsychological test. Low cognitive performance group displayed a greater number of gaze visits in each area of interest and a higher number of fixations. Other than fixation and saccadic measures, Salminen et al. [20] analyzed gaze patterns and fixation heatmaps to predict user confusion when processing information on web interfaces. These visualization techniques were supported with the use of machine learning algorithms and thus, were found to be able to provide a reasonable accuracy in confusion prediction without the input of user attributes.

Despite the vast attempts of utilizing eye tracking in research areas of stress and cognitive performance, much more effort is still needed in analyzing both areas in correlation. Furthermore, as past studies had mainly focused on conventional eye-tracking features relating to fixations and pupil diameter, a wider range of eye-tracking measures should be explored. Therefore, this current study examined further on the possible correlation between stress and cognitive performance. A range of fixation, saccadic and gaze features were also selected to provide a more comprehensive analysis and prediction with the aid of supervised machine learning techniques.

2. Method

2.1 Experiment

In this experiment, the stimulus set consisted of six (6) short passages and three (3) corresponding multiple-choice questions per passage, abstracted from the GRE Verbal Reasoning Practice. The tasks were administered using Tobii Studio Pro version 3.4.8 software. The Tobii X3-120 eye tracker, with a sampling rate of 120Hz, was used to track the eye movements of the participants. The raw eye movement data was analyzed using Python 3.9.7.

Forty three (43) students from Nanyang Technological University, Singapore (NTU) were recruited, aged from 20 to 30 years old (M = 24.2, SD = 2.4). Participants were informed that the experiment's aim was to test their comprehension abilities and there was no mention of stress manipulation or induction to the participants. The experiment consisted control session and stress-induced session. Each session would require the participant to go through 2 reading comprehension tasks, each with a passage and 3 corresponding multiple-choice questions. Before each session starts, calibration was carried out to ensure that the participant's position was at an optimal distance from the monitor for eye-tracking to take place. In th control session, no stress was induced on the participant. As for the stress-induced session, participants were told that they would be assessed based on their speed and accuracy in answering the questions.

2.2 Data Analysis

All the eye-tracking features used in the analysis are condensed in Table 1. There are eight (8) fixation related features and five (5) saccadic realted features, and finally two (2) features that are gaze-related features.

Table 1. Eye-movement measures used in predicting stress and cognitive performance.

Measures	**Unites**	**Description**
Fixation Count	-	Total number of fixations in the given time
Mean Fixation Duration	milliseconds	Average duration of each fixated gaze
Mean Fixation Velocity	Degree/Second	Average angular velocity of fixations
Mean Fixation Stability	-	Average variance of positions of gaze points for fixations
Fixation Time (Passage)	milliseconds	Total time of gaze fixated on passage
Fixation Time (Question)	milliseconds	Total time of gaze fixated on questions
Fixation Count (Passage)	-	Total number of fixated gazes on passage
Mean Fixation Duration	milliseconds	Average duration of each fixated gaze
Mean Saccade Velocity	Degree/Second	Average angular velocity of saccades
Mean Saccadic Amplitude	Degree	Average distance between previous fixation location and current fixation location
Saccade Peak Velocity	Degree/Second	Maximum angular velocity of saccades
Velocity Entropy	-	Measure of uncertainty in the velocity of fixations and saccades
Switches between Passage and Question (SBPQ)	-	Frequency of gaze switch from the passage section to question section, vice-versa
Mean Saccade Velocity	Degree/Second	Average angular velocity of saccades
Mean Saccadic Amplitude	Degree	Average distance between previous fixation location and current fixation location
Saccade Peak Velocity	Degree/Second	Maximum angular velocity of saccades

In this study, LightGBM was used as the main machine learning algorithm to predict both stress and cognitive performance [21]. LightGBM has been proven to be a highly efficient gradient boosting decision-tree model, where it implements leaf-wise tree growth. A series of gradient-boosting decision-tree models and other supervised machine learning models were used in this study as comparative algorithms to determine the effectiveness of LightGBM model. Moreover, Shapley Additive exPlanations (SHAP) is an analysis method that can be used to explain the individual features' prediction [22]. It involves the computation of Shapley values to deduce how much each feature contributed to the prediction, thus, explaining how fairly the prediction is weighted amongst the features used. SHAP weighs each feature based on 3 main properties, which are local accuracy, missingness and consistency. In this study, the SHAP analysis involved the use of SHAP summary plots and dependence plots to interpret the feature importance and dependence. This method is especially effective and fast when applied with tree-based machine learning models, which is a key focus area of the study.

3. Result

3.1 Prediction Results

A 10-fold cross validation was used in the assessment of the selected machine learning algorithms. Four (4) performance metrics were chosen to evaluate the predictive performance of the algorithms, which include the accuracy score, precision score, recall score and F1 score. Dataset had been corrected for imbalanced proportion of predicted variable (stress, cognitive performance) prior to the machine learning processing. Table 2 show the comparative performance of the supervised machine learning algorithms in assessing cognitive performance and predicting stress respectively.

Table 2. Performance of machine learning algorithms in predicting cognitive performance and stress.

	Predicting Performance				**Predicting Stress**			
	Accuracy	Precision	F1	Recall	Accuracy	Precision	F1	Recall
SVM	0.596	0.595	0.603	0.615	0.561	0.550	0.595	0.655
Logistic Regression	0.627	0.617	0.649	0.689	0.545	0.542	0.559	0.581
Decision Tree	0.638	0.658	0.615	0.588	0.641	0.719	0.569	0.487
Random Forest	0.674	0.707	0.646	0.601	0.699	0.747	0.668	0.607
HistGradient Boosting	0.680	0.697	0.664	0.639	0.689	0.709	0.674	0.645
XGBoost	0.731	0.756	0.717	0.687	0.741	0.785	0.720	0.669
LightGBM	0.793	0.831	0.780	0.739	0.825	0.856	0.817	0.785

3.2 SHAP Explanation

SHAP values of each feature were computed for both prediction instances and similarly, the computation was carried out through a 10-fold cross validation. Figure 1 and Figure 2 show the importance of each eye-tracking feature with their global impact for predicting cognitvie performance and stress, respectively.

For SHAP sammry plot, each dot represents one SHAP value for a specific feature and the figure can analysed as such. 1) The colours of each dot represents the value of the feature, with the spectrum from blue (low magnitude) to red (high magnitude); 2)

The vertical axis is sorted according to the importance of the eye-tracking features, with the feature of highest importance at the top (e.g., Saccade Count) and feature of lowest importance at the bottom (e.g., FC_P); 3) The horizontal axis indicates the SHapley values with reference to its baseline score of 0, and it signifies the effect of each feature in predicting cognitive performance and stress (positive SHAP values improves prediction of correct answers/stress state, negative SHAP values predicts wrong answers/non-stress state); 4) The violin plot represents the distribution of data points of each feature within the dataset.

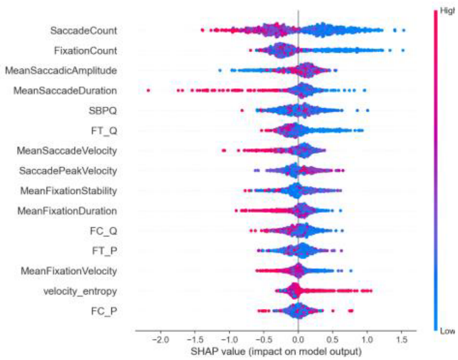

Figure 1. SHAP summary plot for cognitive performance prediction.

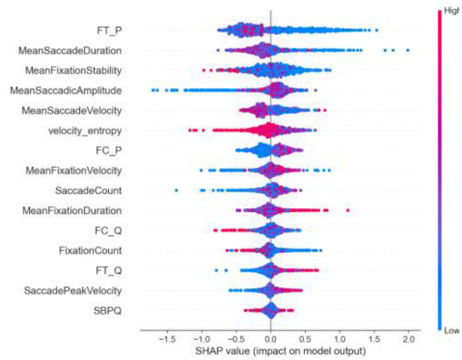

Figure 2. SHAP summary plot for stress prediction.

To better understand how each of the eye-tracking features contribute to assessing cognitive performance and predicting stress, the dependence plots of the top 8 most important features were plotted as seen in Figures 3 and 4. In Figure 3, the most important feature in assessing cognitive performance is saccade count. From the dependence plots, higher number of saccades is associated with low level of cognitive performance as seen from the gradual decrease in SHAP values as saccade count increases. The second most important feature is fixation count. It has a similar trend as saccade count and beyond a count of 100, the SHAP values become negative, indicating a higher probability in predicting low cognitive performance level. The third feature is mean saccadic amplitude. A higher saccadic amplitude of value above 4 degrees is more probable to predict correct answers and an amplitude below 4 degrees is more probable to predict wrong answers. The fourth feature is mean saccade duration. For shorter saccades that are less than 50 milliseconds, SHAP values are high and thus, it increases the prediction probability of participants giving correct answers, showing higher level of cognitive performance. The fifth feature is the gaze switches between passage and questions. Even though there may be no obvious association that is observed from the violin plot in Figure 1, but the dependence plot does indicate that at slightly below 8 gaze switches, it has a higher probability in predicting low cognitive performance level as the SHAP values are significantly lower. Whereas when slightly above 8 gaze switches, the SHAP values increases sharply, signifying an increase in probability of high cognitive performance prediction. The sixth feature is fixation time on the questions. Shorter duration of fixation on the questions improves the prediction of high cognitive performance. Beyond a fixation time of about 25,000 milliseconds, it becomes more probable in predicting low cognitive performance. The seventh feature is mean saccade velocity. Faster saccades predict a lower cognitive performance level in overall. The eighth feature is saccade peak velocity. The dependence plot in Figure 3 shows that with saccade peak velocity of slightly less than 120 degrees/second, the prediction probability of low cognitive performance level increases, as seen from the increasingly negative SHAP values. When increased slightly above 120 degrees/second, the SHAP values increases and become highly positive, indicating increased potential of high cognitive performance prediction.

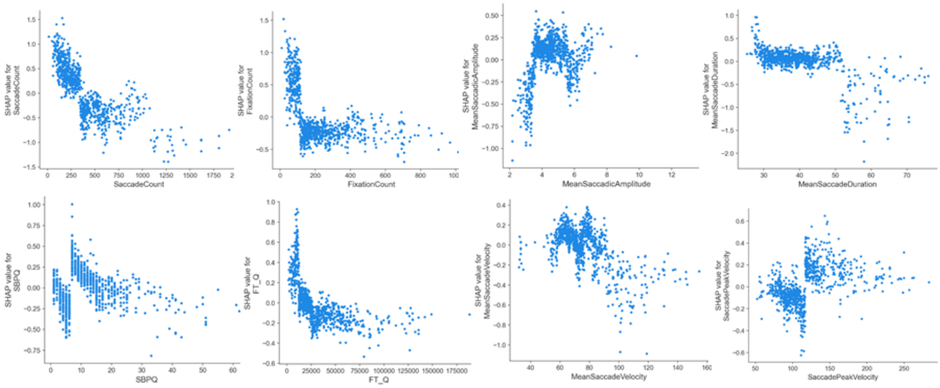

Figure 3. Dependence plots of top 8 most important features in predicting cognitive performance.

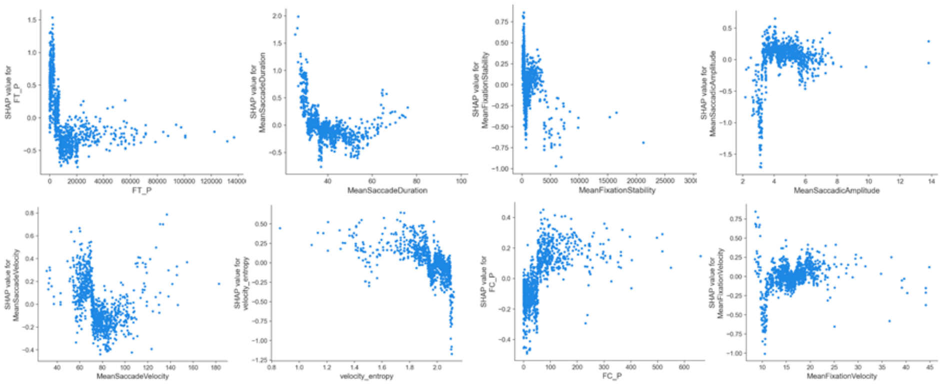

Figure 4. Dependence plots of top 8 most important features in predicting stress.

In Figure 4, the most important feature in predicting stress states is fixation time on passage. Shorter duration of fixation on the passage increases the probability of stress prediction. Beyond 5000 milliseconds of fixation, the SHAP values decrease sharply, and it signifies an increase in prediction of non-stress state. The second most important feature is mean saccade duration. Shorter saccades below 40 milliseconds have higher probability in predicting the presence of stress. The third feature is mean fixation stability. From both the violin plot and dependence plot, there is no significant trend observed but in general, with less stable fixation, there is a slight increase in prediction probability of stress. The fourth feature is mean saccadic amplitude, beyond 4 degrees of amplitude, there is significant increase in SHAP values, indicating that it is more probable to predict the presence of stress for higher saccadic amplitudes. The fifth feature is mean saccade velocity. Within 60 to 100 degrees/seconds, there is a negative correlation between the probability in predicting stress and saccade velocity. Slower saccades are correlated with higher probability in stress prediction. The sixth feature is velocity entropy. From the violin plot in Figure 1, it can be observed that at significantly high entropy values, the SHAP values decrease rapidly, indicating higher probability in predicting non-stress state at high velocity entropy. The seventh feature is fixation count on the passage. Above fixation count of approximately 50, SHAP values show an increase and hence, the probability in predicting stress also increases. The eighth feature is mean fixation velocity. Faster fixations show a slight increase in the predicting probability of stress.

4. Discussion

In this study, eye-tracking features were fitted into supervised machine learning algorithms to assess cognitive performance level and predict stress. First, cognitive performance level was measured by assessing based on ability to answer the questions in the reading comprehension tasks correctly. Second, stress states were pre-determined through sessions under control settings and sessions where stress was intentionally induced. One limitation is the process of stress manipulation as the process was carried out verbally through constant reminders of the need to meet test expectations and this form of stress induction might be perceived differently by different individuals.

LightGBM was seen to be the most promising machine learning model for the prediction of stress and cognitive performance. Based on the evaluation metrics computed, LightGBM outperformed all the comparative machine learning models, including the other gradient-boosting decision-tree models. This is consistent with the findings from Ke et al. [21], where LightGBM was also found to be significantly more outstanding.

In this study, SHAP was used to explain the effects of each eye-tracking features as predictive features of cognitive performance and stress. From the results obtained, saccadic set of features are seen to have a stronger performance than the fixation set of features. However, the gaze features (Switch between Passage and Question (SBPQ) and velocity entropy) have varying prediction performance. Gaze switches performed better in assessment of cognitive performance, but it did not show significant effect in stress prediction. In the contrary, velocity entropy performed well in stress prediction but there was no obvious significance when assessing cognitive performance.

For stress prediction, the current study predicted that individuals under stressed conditions would have a greater number of fixations on passage. These findings correspond to the previous studies as it was also indicated that an individual fixates more under the stimulation of stress [10]. This might have resulted from the expectation to perform better under stress, hence leading to the individual being more focused on the passage details. In addition, in terms of saccades, it was found that stressed students displayed more saccades, which were shorter and slower. The gaze-related features were not significantly indicative in this prediction due to participants having different responses to the presence of stress, and the frequency of gaze switches could depend on which subject (passage/question) the participants had difficulties understanding.

In the assessment of cognitive performance, it was discovered that individuals that displayed high cognitive performance (eg: answering the comprehension questions correctly) had a smaller number of fixations and shorter fixated period on the questions. Therefore, those of lower cognitive performance level generally had more fixations and they fixated longer and slower on the questions. This did not tally with the findings of Tao et al. [12], which could have resulted because the participants who were unable to answer the questions required more attention or focus to understand the questions. As for saccades, participants of high cognitive performance level had less saccades and the saccades were of higher amplitude. A possible explanation for this observation is that the participants had a better understanding of the comprehension tasks, hence they had less fixations, resulting in less movements. In terms of gaze switches between passage and question, participants with better cognitive performance were observed to have more than 8 switches, indicating a higher tendency to cross-reference more frequently between the passage and question as during their information processing stage.

From the assessment of results above, there are correlations that can be drawn between several features. In terms of stress prediction, shorter saccades were seen to be coupled with slower saccades when stress was induced. Saccade count also showed similar trend as saccadic amplitude, where increasing saccade count and saccadic amplitude improves the prediction of stress induced. This relation is significant as it may indicate that the participants displayed increasing level of anxiety when stress was induced, resulting in more erratic eye movements. In the case of cognitive performance prediction, a larger number of saccades and longer saccade duration predict lower cognitive performance. On the other hand, a larger number of fixations were also associated with longer fixation duration at low cognitive performance level. These relations may signify that student with better cognitive performance was able to focus and understand the comprehension tasks quickly with minimal eye movements.

From the analysis of feature behaviours in both prediction cases, there is no direct causal relationship that can be inferred between stress and cognitive performance, but there are certain features (e.g., Saccade Count) that could possibly link the presence of stress with low cognitive performance.

5. Conclusion

This study evaluated the viability of using eye-tracking features to predict stress and cognitive performance of students, with the help of LightGBM model and SHAP analysis. The results indicated that LightGBM model was the best performing algorithm in both predictions as proven by its outstanding scoring based on the performance metrics calculated. According to the SHAP analysis, most of the saccadic features outperform the fixation features. Students under stressed conditions generally had more fixations and saccades, and they displayed saccades with larger amplitude. These results suggest that under stress situations, students tend to display signs of anxiety, leading to more erratic eye movements. For students of lower cognitive performance level, they also had greater number of fixations and saccades, but the fixations were observed to be longer and slower than those with better cognitive performance. It suggests that students with lower level of cognitive performance may require more effort and time to process information. The higher proportion of gaze switches amongst the students with better cognitive performance can also possibly highlight that these students tend to cross-reference more between the passage and question to help with their understanding of the comprehension task. Limitations of the study include the lack of justification and methods to establish possible correlations between stress and cognitive performances. Further studies can also consider incorporating personal information to improve the prediction accuracy, and expand testing to other subjects/ materials. This will facilitate the growth of personalized learning services for industry and academia. With emphasis on transdisciplinary applications in education, the findings of this study provide insights for desiging user-centered services and enhancing learning performance in future e-learning systems.

Acknowledgement

This work was supported by Singapore Maritime Institute Research Project (SMI-2021-MA-03).

References

1. Kogler, L., et al., Psychosocial versus physiological stress—Meta-analyses on deactivations and activations of the neural correlates of stress reactions, *Neuroimage,* Vol. 119, 2015, pp. 235-251.
2. B.B. Baltes et al., *Work across the lifespan*, Academic Press, London, 2019.
3. Scott, S.B., et al., The effects of stress on cognitive aging, physiology and emotion (ESCAPE) project, *BMC psychiatry,* Vol. 15, 2015, pp. 1-14.
4. Y. Shi and S. Qu, Cognitive Ability and Self-Control's Influence on High School Students' Comprehensive Academic Performance, *Frontiers in psychology*, 2021, 783673.
5. P. Morgado and J.J. Cerqueira, The impact of stress on cognition and motivation, *Frontiers in Behavioral Neuroscience*, 2018, 326.
6. A. Mahapatra and P. Sharma, Education in times of COVID-19 pandemic: Academic stress and its psychosocial impact on children and adolescents in India, *International Journal of Social Psychiatry,* Vol. 67, 2021, pp. 397-399.
7. C. Yang, A. Chen, and Y. Chen, College students' stress and health in the COVID-19 pandemic: The role of academic workload, separation from school, and fears of contagion, *PloS one,* Vol. 16, 2021, e0246676.
8. P. Hidalgo-Andrade, C. Hermosa-Bosano, and C. Paz, Teachers' mental health and self-reported coping strategies during the COVID-19 pandemic in Ecuador: A mixed-methods study, *Psychology Research and Behavior Management,* Vol. 14, 2021, 933.
9. D. Pajarianto, Study from home in the middle of the COVID-19 pandemic: analysis of religiosity, teacher, and parents support against academic stress, *Talent Development & Excellence*, Vol.12, No.2s, 2020, pp. 1791-1807.
10. N. Herten, T. Otto, and O.T. Wolf, The role of eye fixation in memory enhancement under stress–An eye tracking study, *Neurobiology of learning and memory,* Vol. 140, 2017, pp. 134-144.
11. C.M. Schulz, et al., Eye tracking for assessment of workload: a pilot study in an anaesthesia simulator environment, *British journal of anaesthesia,* Vol. 106, 2011, pp. 44-50.
12. L. Tao, et al., Eye tracking metrics to screen and assess cognitive impairment in patients with neurological disorders, *Neurological Sciences,* Vol. 41, 2020, pp. 1697-1704.
13. C. Jyotsna, and J. Amudha. *Eye gaze as an indicator for stress level analysis in students*. *2018 IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pp. 1588-1593.
14. C. Hirt, M. Eckard, and A. Kunz, Stress generation and non-intrusive measurement in virtual environments using eye tracking, *Journal of Ambient Intelligence and Humanized Computing,* 2020, Vol. 11, pp. 5977-5989.
15. A. Sanchez et al., Attentional disengagement predicts stress recovery in depression: an eye-tracking study, *Journal of abnormal psychology,* Vol. 122, 2013, pp. 303-313.
16. B. Simonovic, et al., Performance under stress: An eye-tracking investigation of the Iowa Gambling Task (IGT), *Frontiers in Behavioral Neuroscience*, 2018, 217.
17. A. Stankovic, M.R. Aitken, and L. Clark. An eye-tracking study of information sampling and decision-making under stress: Implications for alarms in aviation emergencies. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 2014, https://doi.org/10.1177/1541931214581027.
18. C.-Y. Wang, M.-J. Tsai, and C.-C. Tsai, Predicting cognitive structures and information processing modes by eye-tracking when reading controversial reports about socio-scientific issues, *Computers in Human Behavior,* 2020, Vol. 112, 106471.
19. M. Borys, and M. Plechawska-Wójcik, Eye-tracking metrics in perception and visual attention research, *European Journal of Medical Technologies,* Vol. 3, 2017, pp. 11-23.
20. J. Salminen, et al. Confusion prediction from eye-tracking data: experiments with machine learning. *Proceedings of the 9th International Conference on Information Systems and Technologies*. 2019, pp.1-9.
21. G. Ke et al., LightGBM: A highly efficient gradient boosting decision tree, *Advances in neural information processing systems,* Vol. 30, 2017.
22. C. Molnar, *Interpretable machine learning*. Lulu. com, 2020.