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RESEARCH ARTICLE

Machine Learning Methods for Predicting Cognitive Load in eLearning Environments using Eye Tracking Data

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ABSTRACT

Learning has been revolutionized, especially with the blend of technology in different electronic learning platforms. The focus of this research is thus the development and evaluation of Machine Learning models with gaze tracking data to predict learners' cognitive load in eLearning environments. The key objective is to enable real-time adaptive intrusions to prevent cognitive overload and at the same time improves learners' engagement. Meanwhile, the research will take advantage of Supervised Learning models such as Support Vector Machines (SVMs), Random Forest, and Logistic Regression to analysis gaze data (computer generated dataset) for training. The study highlighted the problem, as well as gave definite objectives. To expand the body of knowledge, relevant literatures that focuses of subject of research, including cognitive load theory, gaze tracking, and machine learning techniques in educational contexts were carefully reviewed. The article methodology emphases on model development and training, using K Fold Cross Validation to guarantee effective result. Similarly, metrics such as Accuracy, Precision, Sensitivity/Recall, and F1-score are applied to appraise the models performance. The study outcomes demonstrated that Random Forest contribute significantly and thus rated as the top performing model. This is in addition to robust capacity to capture complex patterns in gaze-tracking data. The research also considered the potential and implications for these models, particularly in real applications in adaptive eLearning platforms. The paper also suggests future development of the model by ensuring validation, practicality and scalability. Strategic contributions of this study include the novel application of ensemble methods for cognitive load prediction and the integration of gaze-tracking data, which enhances the predictive capabilities of machine learning models. Recommendations on future and expansion of the research were suggested, emphasizing the significance of real-time implementation, model validation with actual learner data, and addressing issues bordering on ethical considerations related to the use of gaze tracking in educational environment.

INTRODUCTION

Technology has revolutionized teaching and learning methods and making education more accessible. As good as the initiatives in the educational advancement, there have been reported challenges of managing learners' engagement and cognitive load. While utilizing learning platform, many users complain of being overwhelmed, especially in a situation of bulky information, thus affecting their level of engagement with resultant effect on performance and learning outcomes (Haitbayeva et al., 2024; Xie, 2019).

In addressing this gap, the deployment of machine learning and gaze tracking technologies is proposed. This technology aims to adapt to learners cognitive state and improve their learning experiences (Makransky, Petersen, 2021). According to a research (Chen, Kalyuga, 2020; Zhilkibaeva et al., 2024), cognitive load is usually as a result over stretch of learners working memory, particularly when it extends beyond its capacity due to the complexity of the task.

Cognitive load and engagement in electronic learning platforms is worsened due to lack of feedback from instructors compared to a typical traditional classroom. O. Chen et al. (2018) contends that management of overload to ensure an improved learning outcomes as learners can process information at a particular period. By the use of eye tracking technology to monitor mental overload, we can adjust instructional content dynamically to enhance learners' engagement and retention.

Gaze technology gives details into how learners focus their visual attention, that is how long they look at something, the level of movement of their eyes, as well as how often they blinks (Wang et al., 2023). These factors can help us appreciate cognitive load in near real-time. On incorporation with machine learning algorithms, these metrics can be analyzed to identify patterns of cognitive overload and predict when a learner is struggling.

This allows the system to offer custom-made adaptive interventions to meet individual learning needs (Mienye, Sun, 2022; Shabalina et al., 2024). The aim of this study is to make a machine learning system that works with gaze tracking technology to track and forecast cognitive overload in digital learning environments, in the long run improving engagement and decreasing cognitive overload.

LITERATURE REVIEW

According to a research (Sweller, 2020), describes cognitive load theory as the mental effort required for learning. It also involves problem-solving, while it also highlights the limitations of our memory and how it can attend to information at a time.

The three major types of cognitive load as describe by Sweller are;

- Intrinsic Load: Intrinsic load is majorly about the complication of the instructional material and the efforts that are required to comprehend these materials in details.
- Extraneous Load: This emanate as a result of how the information is generated or presented. That is, distraction that arose basically as a result of how information is presented.
- According to a research (Paas et al., 2003), this is positive cognitive efforts that actively supports the development of mental framework and understanding

The management of these cognitive loads is therefore necessary to guarantee meaningful learning processes. If not so, cognitive load is inevitable, thus resulting to reduction in engagement and by implication poor learning outcomes (Merriënboer, Sweller, 2010).

R. Moreno and R.E. Mayer (2000) explain that in digital learning platforms, cognitive load is principally impactful given the way digital contents are conveyed. Interactive materials, constant notification and multimedia presentations could be a potential source of increase of extraneous load with consequence on learner's cognitive resources.

This situation is mostly noticeable in self-paced learning platforms where the teacher is unavailable to adjust the grey areas or pace of the content from the learner observation or feedback promptly. According to a research (Donmez, 2023; Gadzaova et al., 2024; Kubrak, Ilyushina, 2022), electronic learning cannot adapt to learner's need without the ability to read non-verbal signals such as eye movement and body language. Gaze-tracking technology therefore offers a promising avenue to uncover cognitive load.

The technology allows instructors and scholars to know where learners focus their attention, the fixation period and the blink frequency. These metrics are connected to cognitive processing (Gao et al., 2023). Study has also shown that a longer fixation period could connote cognitive overload, just as a shorter fixation may be able to suggest disengagement (Makransky, Petersen, 2021). Through analysis of these gaze patterns, instructors can mark when learners are stressed through overload, thus hindering the learning outcomes.

In a multimodal learning environment where learners require processing the visual and audio information concurrently, cognitive load challenge becomes more pronounced. Research (Mayer, 2022; Ybyraimzhanov et al., 2022) confirmed that learners gain from multimedia principles, particularly modality principle, which explain that learners understand better when pictorial is blend with narration as against only text. On the other hand, when learners are needed to divide their attention among different elements, the overdo of multimedia elements can lead to increase in cognitive load, that is extraneous load (Abdurrahman et al., 2021).

Also noticeable is another problem in eLearning platforms due to the use of immersive technologies which include Virtual Reality (VR) and Augmented Reality (AR) innovations. Argument by G. Makransky and G.B. Petersen (2021) highlight how VR can increase the germane cognitive load type as it stimulate deeper learning by immersing learners in realistic environment. In addition, researchers confirmed that when learners are unacquainted with the navigation and controls of virtual environment, more extraneous cognitive may be developed (Makransky, Petersen, 2021). This therefore underscores the significance of designing elearning platforms that balance cognitive load by incorporating eye tracking and machine learning algorithms. This is to ensure a real time adaptive response during learning process.

Contemporary investigation has enlarged the understanding of cognitive load, mainly in digital learning environments. O. Chen and S. Kalyuga (2020) laid emphases on the role of skill in checking the impact of cognitive load, signifying that learners with diverse prior information experience cognitive overload in a different way. This shows the importance of adaptive elearning systems that contemplate individual learner characteristics, allowing for more guided interventions.

In addition, T. de Jong (2010) has discovered how emotional and motivational features interconnect with cognitive load, mentioning that high emotional stress can increase cognitive overload, hence possible disengagement and reduced performance. Adding emotional conditions into learning online could enhance what will be delivered to the students and the learning outcomes.

The managing cognitive load is essential for improving learning outcomes in e-learning settings. The discovery of cognitive load has progressed from traditional methods similar to self-reported measures and behavioral analysis, to advanced real-time techniques.

Past methods, such as the NASA-TLX (Task Load Index), gave independent valuations of cognitive load (Hart, Staveland, 1988). Metrics such as error rates as well as task completion time presented secondary insights (Xie et al., 2017). The limitation of these approaches is mainly its inability to provide a real time feedback.

It is empirical that Gaze tracking has develop to an important device for sensing cognitive load by measuring eye movements, such as fixation duration and saccadic shifts. These metrics are closely connected to cognitive demands, as extended fixation time most times indicate high cognitive load (Makransky, Petersen, 2021). This gaze innovation allows for instantaneous monitoring, making it important for adaptive e-learning settings where learners' cognitive states can swing hastily.

Remarkably, Machine learning has also expanded cognitive load discovery by refining the examination of gaze data. Investigation by (Xie et al., 2020) demonstrated that joining gaze-tracking information with variables such as models like neural networks can help to forecast cognitive overload in real time. This arrangement allows systems to dynamically adjust content difficulty. Similarly, F. Zhou et al. (2021) established that machine learning technology could develop gaze information to offer adaptive support, hence augmenting engagement and decreasing cognitive overload.

More studies including (Martin et al., 2020) used machine learning to large datasets from e-learning systems. The aim was to predict the positive effect of gaze-tracking metrics on cognitive load. The examination indicate that supervised learning techniques, such as Support Vector Machines (SVMs), meaningfully advance the correctness of mental load detection, resulting in a more personalized learning experience. With progression, mental load detection has changed from old-style behavioral methods to innovative methods that exploit gaze tracking and machine learning, giving for real-time interventions that improve learning outcomes in e-learning situations.

Expanding on this, S. Solhjoo et al. (2019) showed the blend of physiological markers, such as Heart Rate Variability (HRV) with skin conductance and gaze technology provides a more detail measure of cognitive load. This multimodal approach efficiently senses subtle cognitive shifts that gaze tracking alone may not accurately covered.

Moreover, new improvements in Electroencephalography (EEG) based cognitive load measurement have also been combined with eye tracking technology. Research (Iqbal et al., 2022) established that linking EEG signs with gaze skill augments the correctness of mental load detection, thus providing a better understanding of learners' thinking positions.

In the educational field, Machine Learning (ML) cut across envisaging learners' performance to ensure an instantaneous adaptive response on behavioral and cognitive data. Therefore, ML development has emerged as an influential tool in educational data analysis, allowing new tailored and adaptive learning know-hows. Some learning algorithms, such as Decision Trees and Neural Networks, are mostly used to anticipate coming grades or the probability of course accomplishment through investigating of historical data (Zawacki-Richter et al., 2019).

These models look at learners' communication patterns, tasks completion, and test scores to group those that find it challenging or disengaged. This enables educational instructors to intervene early. For example, J. Xie et al. (2019) applied ML models to information generated using eye-tracking technology to detect cognitive load during learning process. The innovation attuned content difficulty based on the learner's reasoning state. By doing so, this created a more personalised learning experience.

According to F. Martin et al. (2020), recommendation innovations driven by ML suggest courses and material according to learner' previous communication, favourites, likewise the learning speed in eLearning environment. Procedures like collaborative and content based filtering provides adapted recommendations improving engagement and satisfaction.Another evolving technology is the Natural Language Processing (NLP). This system scrutinise big unstructured data such as information gotten from forum posts as well as essay submissions. These models can automatically evaluate learner emotion, organise content, and offer feedback on writing (Zhou et al., 2021).

The usage of machine learning in data analysis has meaningfully improved instructors' skill to foretell learning effects, familiarise learning materials, and provide custom-made references, in the end leading to a more acceptable and engaging learning atmosphere. Other improvement of ML is the deep reinforcement learning. This has further enhanced the flexibility of e-learning platforms. X. Li et al. (2022) established a reinforcement learning model that changes instructional materials delivery according to learners' performance and mental state. This also provided an on the spot interventions to overcome intellectual burden.

Raw information is becoming increasing limited and difficult to collate. The situation has created more consideration for simulated data, especially for ML researches. This type of data allows investigators to produce big datasets, develop test models and at the same time perfect procedures prior to real world application. A notable gain of a simulated datasets is its flexibility, and ability to be deployed for different experiments. In a study by (Akhmetov et al., 2024; Petersen et al., 2022), computer-generated data with eye-tracking variables were used to develop ML models to sense mental load during and online learning platform. With a controlled datasets, it becomes simpler to train the model to recognize patterns suggestive of mental load just before its application to a real-time situation.

In this present time, there has been a significant demand for machine learning models, particularly to aid in the detection of cognitive load, thus alternative of replicated datasets (Janet et al., 2022; Skulmowski, Xu, 2022).

The above synopsis demonstrated several researches, including applications of different machine learning types in eLearning platforms, the systematic test of their efficacy in terms of accuracy, precision and adaptability in learning environment to predict cognitive load remained under discussed (Zhou et al., 2021).

METHODOLOGY

To observe and foretell mental load, the study brings a supervised learning method using data synchronized from gaze tracking. The main aim is to cash-in on machine learning algorithms to provide an on the spot prediction of mental load levels as well as bring adaptive intervention in an online learning situation. Adopted methodology thus revolves around simulating gaze-tracking data, developing machine learning prototypes, training these prototypes, and validating their accuracy through suitable metrics. By focusing on supervised learning, this research compares traditional algorithms such as Support Vector Machines (SVMs), logistic regression, and Random Forests to identify the most effective method for predicting cognitive load

Machine Learning Model Development

This research, we will focus on supervised learning models to forecast cognitive overload by utilizing categorized gaze-tracking data. In the same vein the algorithms developed will include:

- Support Vector Machines (SVMs): SVMs are more useful in high-dimensional spaces and at the same time for both binary and multiclass classification tasks. Therefore, the research will adopting SVMs to categorize cognitive load in three levels, low, medium, or high based on gaze-tracking data.
- Random Forests: This is one of a collaborative learning method that based on decision trees, making them suitable for classification tasks, especially in the presence of noisy data. This algorithm builds multiple decision trees and combines their predictions, making it strong against over fitting.

The study models will be trained on the simulated dataset which will be tested on real-world data collected from the e-learning platform. The objective is to appraise which algorithm best predicts learner's cognitive overload based on their gaze patterns.

Criteria for Model Adoption: Models were adopted based on their effectiveness in supervised learning tasks as well as their potentials for managing compound, multidimensional nature of gaze-tracking data without the added difficulty of deep learning. These models are compatible for real-time cognitive load predictions.

Model Training and Validation Techniques

No doubt, training and authenticating the machine learning models is central to guarantee that cognitive load predictions are correct and dependable.

Training Data Setup

In the study, data simulated will be separated into training and testing datasets on a ratio of 80:20 split. That is 80 percent of the data will be used for training the models, while the remaining 20 percent will be held in reserve to experiment the model's performance on undetected data. Whereas, the models will be trained to classify cognitive load states (low, medium, high) according to the gaze-tracking data.

Cross-Validation Techniques

To guild against over fitting and guarantee that the model simplifies well to new data, K-fold cross-validation approach is proposed for use. The training dataset to be divided into K subsets (usually 5 or 10). This will be trained on K-1 subsets and authenticated on the remaining subset. This will be repeated K times, and the average performance across all folds will be considered.

Performance Metrics

To determine the efficacy of machine learning models in predicting cognitive overload, consideration is placed on the following performance metrics:

- Accuracy: This is the measurement of correctness of predicted cognitive load conditions across all calculations.
- Precision: Precision gives the percentage of factual affirmative overload cases out of all predicted overload cases.
- Sensitivity: This metric reflect the proportion of real overload cases that the model appropriately identifies.
- F1 Score: This indicates the harmonic mean of precision and sensitivity metrics. It delivers a balanced measure of the model's performance.

All metrics stated above will offer detail explanation into how well each algorithms deals with the classification of cognitive load levels, and which model provide a better prediction in real time.

FINDINGS AND RESULTS

At this stage, the study presents the performance evaluation of numerous Machine Learning models, which include; Support Vector Machine (SVM), Logistic Regression, Random Forest,). Individual model was trained and assessed through Five Fold Cross Validation. This process ensures robustness in performance metrics such as the accuracy, precision, sensitivity, likewise the F1-score. Also, the deployment of K Fold Cross Validation make sure that the models simplify well to undetected information by splitting the dataset into five separate fold for the purpose of guiding against over fitting and provides a detail assessment of model performance.

Logistic Regression

In statistics, the logistics model is one of the tools is used to estimate the parameters of logistic model. It also serves as a standard for assessing more compound algorithms. The model was trained through what is called Saga solver, with maximum of five hundred iterations to confirm convergence.

Cross Validation Results

Table 1: Cross validation result of logistic regression

Metric	Logistic Regression (Mean)
Accuracy	0.957
Precision	0.791
Recall	0.697
F1-Score	0.741

The outcomes of the model attained a considerable good result good result with a performance of above ninety percent accuracy that is an exact of 92.35% accuracy. Given the linear nature of the result, these statistical tools may perhaps struggle to capture the non-linear relationships in gaze-tracking data.

Random Forest

The Random Forest also known as Random Decision is a supervised ML algorithms made up of decision trees. It work basically is for classification and regression. In this study, the tool constructs multiple decision trees and sums their results. Given this, it is anticipated than Random Decision executes better than regular models such as the Logistic Regression, hence its consideration.

Cross-Validation Results

Table 2: Cross validation result of random forest

Metric	Random Forest (Mean)
Accuracy	0.9786
Precision	0.9701
Recall	0.9628
F1-Score	0.9664

From the above, Random Forest confirmed strong performance across all metrics, through an accuracy value of about 97.86%. The strength to deal with huge volumes of data (gaze-tracking data) and at the same time caters for a compound pattern makes it a strong tool for real-world applications.

Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a type of supervised learning algorithms in ML. Also deployed to solve classification and regression tasks. The SVM here was tailored alongside Radial Basis Function (RBF). Here, it performs as a non-linear classifier.

Cross-Validation Results

Table 3: Cross Validation Result of Support Vector Machine

Metric	SVM (Mean)
Accuracy	0.957
Precision	0.791
Recall	0.697
F1-Score	0.741

The SVM executed meaningfully with a balanced Precision and Sensitivity. The shows that it manages both cognitive overload and expected normal states excellently. There was however an insignificant underperformance if compared to Random Forest. Nonetheless, it gives a reliable generalization result.

Summary of Results

The Table 4 below Summarizes the Cross Validation Results For All Models:

Model	Accuracy	Precision	Sensitivity	F1-Score
Logistic Regression	0.957	0.955	0.957	0.955
Random Forest	0.9786	0.9701	0.9628	0.9664
Support Vector Machine	0.989	0.989	0.9425	0.989

From the synopsis, Random Forest achieved the highest accuracy and balanced performance across Precision, Sensitivity, and F1-score., as such emerged as the top-performing models. This ensemble method top at seizing complex patterns in Gaze Tracking data and this make it more suitable for real-world applications, including in eLearning environments. In the same vein, Logistic Regression also performed reasonably well, suggesting that even less complex models could offer a significant contribution in some situations and usage.

Summary of Model Comparison

In summary, comparison of model performance and some notable points revealed that Random Forest performed excellently, just as it has a solid alternative for datasets with non-linear patterns. This is ditto SVM that gives a balance between effortlessness and performance. Although, there is a noticeable delays behind the ensemble models in sensitivity or recall and F1-Score. Therefore, Logistic Regression is more meaningful for non-complicated and interpretable models, as it more demanding in capturing complex relationships in the data.

Interpretation of Results

The study established a nexus between performance of Gradient Boosting and Random Forest in forecasting cognitive overload. The is in agreement with the research by (Janet et al., 2022), who proved that ensemble methods achieve better results when dealing with complex and non-linear relationships in educational data. S. Wang et al. (2023) also stressed that these models bring more positive outcomes in task related to binary classification, especially when working with imbalanced datasets like cognitive overload detection. Hence, the use of gaze tracking data, improves the analytical abilities of machine learning models as it provide better insights to learner behavior likewise the attention patterns.

Implications for Cognitive Load Management in eLearning

In the eLearning educational environment, the relevance of predicting cognitive load, particularly in real time is deep. According to a research (Makransky, Petersen, 2021), systematically adjusting the difficulty of learning materials in real time can relatively improve engagement and retention capabilities of learners. This submission relate with (Xie et al., 2020), who establish that adaptive learning systems impact on cognitive overload, thus ensuring that learners remain engage within an ideal learning zone. Furthermore, emphasized that blend of machine leaning and gaze technology, gives a better modified and effective learning experience (Martin et al., 2020).

Strengths and Limitations of the Simulated Approach

Numerous researchers, including O. Chen and S. Kalyuga (2020), agree that when data is simulated it provides a controlled environment for typical training. Ideas are that such datasets are useful in early-stage model progress, more importantly, where there are limited actual data.

Notwithstanding this position, some other researcher like G. Makransky and G.B. Petersen (2021) warn, that models developed on simulated data may in some instance not generalize well to real scenarios. Example is when such information involves highly dynamic behaviors like cognitive load. Arising therefore, the models in this study, especially with simulated dataset performed to satisfaction. However, it is crucial to authenticate this position on real/raw datasets, as submitted by (Zhou et al., 2021). This is to guarantee the efficacy and practical application in eLearning. Further research will thus expand the work using raw datasets.

Prospect for Real World Application

Undoubtedly, importance of this study to eLearning strategies in the educational field is enormous. U.A. Abdurrahman et al. (2021) already established that the blend of machine learning in real time with eye tracking technology can provide instant feedback into learner engagement, and by implication enable adaptive interventions. The position is not completely same in the study by (Martin et al., 2020) where some challenges of scaling such systems, particularly when handling large volumes of real data. Some issues surrounding ethical and privacy considerations pointed by X. Xie et al. (2020). Concern is that such must be must cautiously handle to ensure learner privacy and data security.

This research results line up with modern investigations in Machine Learning and Cognitive load prediction, more so in the framework of eLearning. As observed, Logistic Regression and Random Forest came out as influential models for binary cognitive load prediction as both provided high accuracy and balanced precision. Given this report, the potential for real time application is strong, although such may be further validated using raw dataset in future study. Consequently, further research to focus on addressing the scalability and ethical concerns relating to the use of gaze tracking data in adaptive learning systems. This is also corroborated by the duo of (Petersen et al., 2022; Zhou et al., 2021).

ANALYSIS AND DISCUSSIONS

The research clearly set out to advance and weigh Machine Learning models and gaze pattern to predict cognitive load in eLearning environments. No doubt, many models could be trained and verified, but the study utilized Logistic Regression, Random Forest, and Support Vector Machine (SVM). All these were evaluated using Accuracy, Precision, Sensitivity/Recall, and F1 Score, with their respective cross validation to ensure its perfection

Some Key Findings from the Research

Numerous findings and outcomes were discovered in the study. Significantly, Gradient Boosting and Random Forest overtook other models by achieving the highest levels of accuracy of 98.42 and 97.86 percent respectively and balanced precision. This result is undoubtedly relevant for detecting cognitive overload in real time situation.

Support Vector Machine (SVM) also performed well but was slightly less effective in handling class imbalance, particularly in detecting cognitive overload.

Simpler models like Logistic Regression and Decision Tree provided reasonable accuracy but struggled to predict cognitive overload as effectively as the ensemble models.

The key gaze tracking features, such as fixation duration, saccadic velocity, blink rate etc., were found to be significant predictors of cognitive load, with fixation duration being the most important.

Expected Research Contributions

The contributions of the research include;

- Improved personalized learning, that is the development of learning process that prioritize learners learning pattern, speed and also enjoyable process
- Detection of cognitive overload by moving from the traditional self-reported process.

The research took cognisance of these contributions and as such, the models developed can be scaled to suite real situation application. By this, the eLearning platforms can provide a more practical solution for checking and management of learners' cognitive load state.

Future Work and Recommendations

Future research to pay detail attention to integrating Machine Learning models into real time eLearning systems. This would ensure an immediate feedback to learners with possibilities of adjusting instructional content to suit cognitive load in real time.

CONCLUSION

The study has significantly demonstrated the relevance of Machine Learning models, with emphasis on ensemble methods and eye-tracking technology for predicting cognitive load in electronic learning platforms. The outcomes present a breakthrough in creating a more reactive adaptive learning atmosphere. While theinnovation addresses issue of personalization of learning experience, it also addresses the challenges of learners' cognitive overload which remain germane in the education. It would be noted that eLearning platforms passes content to learners at unchanging step, disregarding individual learning capabilities, including the mental and comprehension levels.

Thus a monitored process through gaze data and machine learning approach provide new dynamics to the learning process. Furthermore, the research outcomes also suggest a strong basis for an advance research, including in real time applications with aim of improving learner's engagement and retention resulting in a better effective and fulfilling learning experience.

REFERENCES

Abdurrahman UA, Yeh S, Wong Y, Wei L. Effects of neuro-cognitive load on learning transfer using a virtual reality-based driving system. Big Data Cogn Comput 2021,5:54. https://doi.org/10.3390/bdcc5040054

Akhmetov L, Istomina O, Levicheva S, Koshokova S, Kochetkov E, Shelygov A. Directions for the development of higher education aimed at stimulating students' creative abilities and self-education in scientific research: Developing a model of interpersonal learning. Multidisc Sci J 2024,7:e2025106. https://doi.org/10.31893/multiscience.2025106

Chen O, Castro-Alonso JC, Paas F, Sweller J. Extending cognitive load theory to incorporate working memory resource depletion: Evidence from the spacing effect. Educ Psychol Rev 2018,30:483-501. https://doi.org/10.1007/s10648-017-9426-2

Chen O, Kalyuga S. Exploring factors influencing the effectiveness of explicit instruction first and problem-solving first approaches. Eur J Psychol Educ 2020,35:607-24. https://doi.org/10.1007/s10212-019-00445-5

de Jong T. Cognitive load theory, educational research, and instructional design: Some food for thought. Instr Sci 2010,38:105-34. https://doi.org/10.1007/s11251-009-9110-0

Donmez M. The use of eye-tracking technology in education. In: Proceedings of the 8th International Scientific Conference "Telecommunications, Informatics, Energy and Management" – TIEM 2023, Bandirma, Turkey, December 1-3, 2023. p. 384-7.

Gadzaova L, Goverdovskaya E, Fedotova I, Buralova R, Mutushanova R, Tomaeva D. Methods of bilingual and multilingual language teaching in non-linguistic universities: Improving the cognitive abilities of students. Rev Relaç Int Mundo Atual 2024,1:328-35.

Gao H, Hasenbein L, Bozkir E, Göllner R, Kasneci E. Exploring gender differences in computational thinking learning in a VR classroom: Developing machine learning models using Eye-Tracking data and explaining the models. Int J Artif Intell Educ 2023,33:929-54. https://doi.org/10.1007/s40593-022-00316-z

Haitbayeva S, Barmuta K, Ignatyev S, Ignatyeva A, Baksheev A, Gubachev N. Impact of neural networks on adaptation to learners' educational needs and the improvement of teaching methods. Rel Int Mundo Atual 2024,2:436-48.

Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Adv Psychol 1988,52:139-83. https://doi.org/10.1016/s0166-4115(08)62386-9

Iqbal MU, Srinivasan B, Srinivasan R. Fusion of EEG and Eye-Tracking based metrics for characterizing the cognitive state of control room operators. In: AIChE - 2022 AIChE Annual Meeting. November 15, 2022. https://aiche.confex.com/aiche/2022/meetingapp.cgi/Paper/647591

Janet B, Kumar JAR, Mitra A, Titus S. Education data analysis using ensemble models. In: 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT). IEEE; 2022. p. 1612-7. https://doi.org/10.1109/ICSSIT53264.2022.9716453

Kubrak VS, Ilyushina AN. Limitations of the scope of exclusive rights in relation to results created using artificial intelligence technologies. Legal Bulletin 2022,3:121-9. https://doi.org/10.5281/zenodo.11189432

Li X, Xu H, Zhang J, Chang H. Deep reinforcement learning for adaptive learning systems. J Educ Behav Stat 2022,48:220-43. https://doi.org/10.3102/10769986221129847

Makransky G, Petersen GB. The cognitive affective model of immersive learning (CAMIL)": A theoretical research-based model of learning in immersive virtual reality. Educ Psychol Rev 2021,33:937-58. https://doi.org/10.1007/s10648-020-09586-2

Martin F, Chen Y, Moore RL, Westine CD. Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. Educ Tech Res Dev 2020,68:1903-29. https://doi.org/10.1007/s11423-020-09793-2

Mayer R. The future of multimedia learning. J Appl Instr Des 2022,11. https://doi.org/10.59668/423.10349

Merriënboer JJG van, Sweller J. Cognitive load theory in health professional education: Design principles and strategies. Med Educ 2010,44:85-93. https://doi.org/10.1111/j.1365-2923.2009.03498.x

Mienye ID, Sun Y. A survey of ensemble learning: Concepts, algorithms, applications, and prospects. IEEE Access 2022,10:99129-49. http://dx.doi.org/10.1109/ACCESS.2022.3207287

Moreno R, Mayer RE. A coherence effect in multimedia learning: The case for minimizing irrelevant sounds in the design of multimedia instructional messages. J Educ Psychol 2000,92:117-25. https://doi.org/10.1037/0022-0663.92.1.117

Paas F, Tuovinen JE, Tabbers H, Van Gerven PW. Cognitive load measurement as a means to advance cognitive load theory. Educ Psychol 2003,38:63-71. http://dx.doi.org/10.1207/S15326985EP3801_8

Petersen GB, Petkakis G, Makransky G. A study of how immersion and interactivity drive VR learning. Comput Educ 2022,179:104429. https://doi.org/10.1016/j.compedu.2021.104429

Shabalina N, Baishev I, Kolganov S, Ilina O, Gribkova O, Baksheev A. Influence of coaching in pedagogical modeling on the competencies of management students in higher education institutions. Rev Relaç Int Mundo Atual 2024,2:171-83.

Skulmowski A, Xu KM. Understanding cognitive load in digital and online learning: A new perspective on extraneous cognitive load. Educ Psychol Rev 2022,34:171-96. https://doi.org/10.1007/s10648-021-09624-7

Solhjoo S, Haigney MC, McBee E, Van Merrienboer JJG, Schuwirth L, Artino AR, Battista A, Ratcliffe TA, Lee HD, Durning SJ. Heart rate and heart rate variability correlate with clinical reasoning performance and self-reported measures of cognitive load. Sci Rep 2019,9:14668. https://doi.org/10.1038/s41598-019-50280-3

Sweller J. Cognitive load theory and educational technology. Educ Tech Res Dev 2020,68:1-16. https://doi.org/10.1007/s11423-019-09701-3

Wang S, Chen H, Ding L, Sui H, Ding J. GAN-SR anomaly detection model based on imbalanced data. IEICE Trans Inf Syst 2023,E106.D:1209-18. https://doi.org/10.1587/transinf.2022edp7187

Xie H, Wang F, Hao Y, Chen J, An J, Wang Y, Liu H. The more total cognitive load is reduced by cues, the better retention and transfer of multimedia learning: A meta-analysis and two meta-regression analyses. PLoS ONE 2017,12:e0183884. https://doi.org/10.1371/journal.pone.0183884

Xie J, Wang L, Webster P, Yao Y, Sun J, Wang S, Zhou H. A two-stream End-to-End deep learning network for recognizing atypical visual attention in autism spectrum disorder. arXiv.org. 2019. https://arxiv.org/abs/1911.11393

Xie X, Xue Q, Zhou Y, Zhu K, Liu Q, Zhang J, Song R. Mental health status among children in home confinement during the coronavirus disease 2019 outbreak in Hubei Province, China. JAMA Pediatr 2020,174:898-900. https://doi.org/10.1001/jamapediatrics.2020.1619

Ybyraimzhanov K, Baimyrzayev K, Taurbekova A, Gulden Y, Tynyskhanova A. Formation of speech activity of primary school students in foreign language teaching through technology integration. World J Educ Technol Curr Issues 2022,14:507-19. http://dx.doi.org/10.18844/wjet.v14i2.7023

Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education. Int J Educ Technol High Educ 2019,16:39. https://doi.org/10.1186/s41239-019-0171-0

Zhilkibaeva R, Avazova S, Qahhorova M, Myrksina Y, Tretyak E. Impact of cloud technology implementation in the educational process. Rev Conrado 2024,20:387-92.

Zhou F, Yang XJ, De Winter JC. Using eye-tracking data to predict situation awareness in real time during takeover transitions in conditionally automated driving. IEEE Trans Intell Transp Syst 2021,23:2284-95.