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Signal-Based Cognitive State Analysis for Adaptive E-Learning Environments

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Abstract

The adaptive e-learning systems are increasingly based on the behavioural interaction data to personalise the delivery of the content, but this data can only give limited information on the cognitive state of the learner taken. This paper is aimed at addressing this shortcoming by proposing a signal-based cognitive state analysis model where real-time adjustment of e-learning negotiable settings can be made with the application of physiological cues to detect alterations. It is based on a closed-loop adaptive learning system with the proposed methodology combining the signal acquisition, preprocessing and feature extraction with a data-driven model of cognitive state. Raw physiological data are initially filtered and converted to obtain discriminative characteristics of time and frequency with which to describe changes in learner attention and mental workload. Those characteristics are then employed to train a supervised learning model to infer discrete candidate mental states which in turn are translated into adaptive learning interventions based on rule constrained decision logic. Experimental analysis on a controlled learning dataset shows that the suggested signal-based model shows high cognitive state classification than baseline methods that use traditional interaction measures. Moreover, it was found that cognitive-based adaptation leads to a study improved engagement and learning efficiency of learners, which indicates the usefulness of incorporating the analysis of physiological signals into adaptive e-learning systems. The suggested framework offers a scale-up and expansion framework of intelligent learning environments facing the next-generation that need precise cognitive cognizance and dynamism in real-time.

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Introduction

The increasing trend of online and digital education platforms has added pressure on the need to have smart e-learning systems that can adjust the learning materials to teach each student individually. The traditional adaptive learning systems mostly use overt behavioural cues like click stream activity, scores on assessments and time on task measurements to determine learner engagement and progress.[7, 8] Even though these measures are easy to obtain, they only give indirect and delayed information about the internal cognitive process of the learner, which restricts the capacity of the system responding to the change in attention, cognitive load, and mental fatigue.[6] Physiological sensing technologies have advanced recently to allow the first-hand observation of cognitive and affective processes based on the processes of neural and autonomic responses. Electroencephalography (EEG), electrocardiography (ECG), and galvanic skin response (GSR) are physiological measures that have been shown to correlate well with cognitive processes like attention, workload and engagement.[1, 2, 11] In comparison with interaction-based measures, such signals provide informative content on learner cognition at a fine level and in real-time, which means that they are highly appropriate in adaptive systems where feedback should be obtained in a timely and correct manner.[9, 10] In the signal processing perspective, it is also difficult to retrieve credible cognitive information in crude physiological information because of noise, artefacts, inter-subject variations, and non-stationary biosignals.

Proper analysis of the cognitive state therefore must have a well-designed processing pipeline and involve the collection of signals, preprocessing, feature extraction and may include a powerful model.[3, 4, 12] Although the idea of signalling estimate of cognitive states has been researched in a large number of studies, most of them have centred on classification accuracy in individual experiments and do not incorporate cognitive inference in the adaptive learning decision making.[5] Therefore, the feasible opportunities of analysing physiological signals in real-time and adapting to e-learning situations have not been explored fully. In addition, extant adaptive learning systems which utilise cognitive or affective feedback tend to follow fragmented architectures wherein signal processing, cognitive modelling and adaptation logic might be loosely coupled systems.[6, 7] These architectures restrict reproducibility, scalability, and deployability especially in practice in learning environment where computational efficiency and system consistency is needed. These constraints indicate a need to have a common signal-processing based architecture making a close integration of physiological signal analysis and adaptive learning mechanisms.[5, 9] This paper gives a comprehensive signal based cognitive state analysis framework in adaptive e-learning environment. The architecture is proposed to provide a systematic mixture of physiological signal acquisition, preprocessing and feature extraction and a feature-based cognitive state modelling scheme that makes use of time-domain representations, frequency-domain representations and time-frequency-domain representations.[3, 4] The deducted mental states are built into a closed-loop adaptive learning system, which allows the personalization in real-time by adjusting dynamically the content pacing, difficulty, and the delivery of feedback.[6, 10] The proposed approach is clearly seen to be effectively validated in experimental works which indicate the apparent benefits of physiological signal-based adaptation as compared to the traditional interaction-driven ones regarding the accuracy of cognitive states recognition and learning response [1, 5, 12] The rest of this paper has been structured in the following manner. Section 2 is the review of the related work in the field of cognitive state estimation, signal processing techniques, and adaptive learning systems. Section 3 outlines the suggested methodology, consisting of system architecture, signal processing and cognitive modelling. Section 4 describes the experimental set up and Section 5 gives the results and the performance analysis. Section 6 presents implications and limitations of the proposed framework, and Section 7 is the conclusion of the paper that provides directions of future research.

Related Work

Physiological signals have widely been used to estimate cognitive states because they are able to acquire latent neural and affective processes that are not directly observed by way of learner interaction.[1, 2, 5] The most popular modality of measuring cognitive load, attention, engagement, and mental fatigue has been the electroencephalography (EEG) due to the sensitivity of neural activity and time resolution.[3, 9, 10] It has been demonstrated in many studies that frequency differences in spectral power changes in the theta, alpha, and beta bands have a close relationship with alterations in cognitive load and states of attention.[3, 12] Besides EEG, peripheral physiological indicators such as the electrocardiography (ECG), galvanic skin response (GSR) and photo plethysmography (PPG) have been utilised to determine cognitive and affective states of the brain, based on the physiological response of the autonomic nervous system.[1, 11] Recent studies have also explored the multimodal signal fusion schemes to build the robustness and sensitivity to noise especially in practical learning conditions.[2, 5] Even with these developments, there are numerous current methods that have focused on the controlled experimental scenario and are incapable of seamlessly integrating with adaptive learning systems.[6]

In signal processing terms, previous efforts have been mostly concerned with the extraction of discriminative signals in physiological signals using a series of steps comprising of preprocessing steps and transformation steps.[3, 4] Typical pre-processing methods are band pass filtering, artefact elimination, and normalisation of signals and then finding features in time, frequency, or time-frequency domains.[3, 12] Band energy characteristics as well as wavelet-based representations and statistical measures, power spectral density estimates have been broadly used in classical machine learning models.[3] In more recent works, hierarchical representations have been developed to be learned directly on raw signals or minimally processed signals with the use of convolutional or recurrent neural networks.[4, 5] Although those models tend to show better classification performance, they usually demand more computational and lower interpretability, which makes it harder to apply them in real-time adaptive business practises.[4, 9] In addition, most research lacks a clear connexion between signal-level modelling options and downstream adaptive decision mechanisms.[5] Traditional adaptive learning system has been based on the data of behavioural interaction, the result of assessment process and the personalization strategies based on rules to optimise the learning content.[7, 8] As learning analytics have expanded, predictive and model-based data-driven methods of learning performance and engagement have emerged.[7] An even smaller body of work has also investigated how cognitive or affective feedback (based on physiological cues) can be used to direct adaptation in e-learning settings, including in setting the level of learning content or learning pace.[6, 10] Nevertheless, these systems tend to couple the cognitive state inference and adaptation into loosely coupled subsystems, hence producing fragmented structures.[6, 7] In addition, most current literature focuses on the educational performance of system but has minimal technical information on the signal acquisition, feature modelling and system level integration and limits reproducibility and scalability.[5] A comparative summary of the representative studies is performed in Table 1 to place these limitations in context by giving the modalities of the signal used, the method of extracting the features, the type of modelling, and major limitations. The given comparison shows that there is a research gap with respect to coherent, signal-processing-based models that attempt to answer cognitive state estimation and adaptive decision-making in intelligent e-learning setups jointly.[5, 9]

Proposed Methodology

System Architecture and Signal Acquisition

The suggested methodology is a signal processing-oriented unified architecture that can allow the real-time analysis of cognitive state and adaptive learning. The complete system adheres to the design of a modular but highly coupled pipeline, starting with acquisition of physiological signals and continuing with signal preprocessing, feature extraction, modelling of the cognitive state and adaptive control of decision-making. This end-to-end is a design that verifies that raw biosignals have a controlled conversion to actionable learning adaptations but still has the ability to stay computationally efficient and system coherent. At the input stage the system receives physiological inputs which have been known to be indicative of cognitive and affective processes. The electroencephalography (EEG) signals are mainly taken into account in this piece of work because they are very time-resolved and are highly correlated with the cognitive load and attention. Moreover, the peripheral physiological activity may be included, like the electrocardiography (ECG) and galvanic skin response (GSR), to record sympathetic autonomic responses of engagement and mental effort. The modalities of these signals give multimodal representation of cognition of a learner that makes it more resilient to noise and personal variation.

Wearable sensors that do not involve any invasive action are used to record physiological signals, which are then digitised at sampling rates that are modality-specific to maintain the important temporal variations. Signal acquisition module will interfere with sensors, time stamping and modality synchronisation. Temporal registration is of particular importance, especially when many sources of physiological types of data are monitor able at once, since cognitive state estimation depends

Table 1: Comparison of Related Work on Cognitive State Estimation and Adaptive Lear6ning Systems

Study Category	Signal Types	Feature Extraction Methods	Modeling Approaches	Key Limitations
EEG-based cognitive load analysis	EEG	Band power, PSD, wavelet coefficients	SVM, k-NN, Random Forest	Limited generalization; often task-specific and offline
Peripheral physiological signal analysis	ECG, GSR, PPG	Time-domain statistics, HRV features	Classical ML classifiers	Weak cognitive specificity; sensitive to noise and context
Multimodal cognitive state estimation	EEG + ECG + GSR	Feature fusion, time-frequency features	Ensemble models, shallow neural networks	Increased complexity; synchronization challenges
Deep learning-based signal modeling	EEG, multimodal signals	End-to-end learned representations	CNN, LSTM, hybrid DL models	High computational cost; low interpretability
Interaction-driven adaptive learning systems	Clickstream, quiz data	Behavioral metrics	Rule-based systems, predictive models	No direct cognitive insight; delayed adaptation
Cognitive-aware adaptive e-learning systems	Physiological + interaction data	Handcrafted cognitive indicators	Hybrid ML frameworks	Loose coupling between cognition inference and adaptation

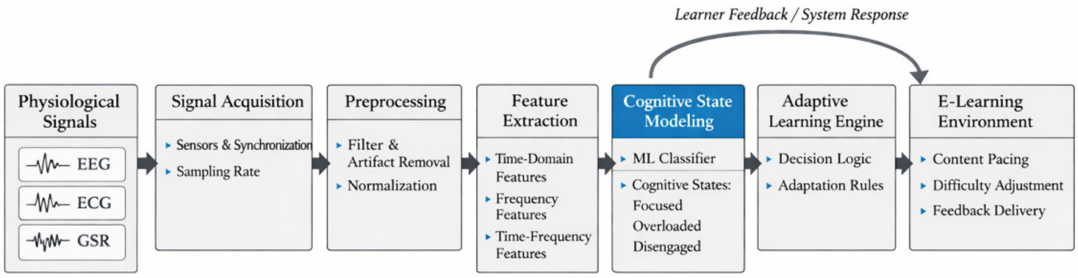

Fig. 1: Overall system architecture of the proposed signal-based cognitive state analysis framework for adaptive e-learning.

on consistent feature representations that have been gained through concordant streams of data. However, aside inter-signal synchronisation, the architecture synchronises physiological data with learning events that take place in the e-learning environment. The learning events like presentation of the content, interaction of the users and assessment activities are recorded with accurate time stamp and mapped to physiological segments of the signal. Such alignment provides the system with the opportunity to match cognitive state changes with particular learning contexts on which meaningful adaptation decisions are based.

Figure 1 shows the entire system architecture that provides the flow of information starting with the acquisition of physiological signals through preprocessing and feature extraction and then the models of cognitive states to the adaptive learning engine. The e learning environment is connected to the cognitive state modelling component by a closed-loop feedback mechanism that enables the model to keep on updating its inference as the learner responds and the system takes action in response to the learner. This construction will be able to ensure that the cognitive state analysis and adaptive learning are implemented as a unit process and not as separate aspects.

Distribution of Features and Classifier Training.

The signals obtained by wearable sensors are physiological and this means that noise, motion artefact and baseline drift inherently affect the signals obtained thus, acting negatively on the validity of cognitive state prediction. In order to reduce the effects these factors, the proposed structure uses a structured signal preprocessing pipeline that aims at improving the quality of signals but maintains cognitively relevant information. Removal of noise and artefacts is initially done to suppress unwanted signal that would be formed as a result of sensor motion, noise, environmental interference and physiological artefacts. Statistical thresholding, adaptive filtering or component-based decomposition artefact suppression methods can be used depending on the signal modality to remove non-informative portions of a signal. After the removal of the artefacts, the physiological signals are band-limited and normalised. Frequency components of interest to cognitive activity are isolated using band pass filtering and low-frequency drift and high-frequency noise are reduced. The mathematical process of filtering can be denoted without the impulse response of the chosen philtre as the convolution of the raw signal with the impulse response of the philtre as is represented in (1):

$$x_f(t)=x(t)*h(t), \tag{1}$$

where $x(t)$ denotes the raw physiological signal, $h(t)$ represents the impulse response of the filter, and $x_f(t)$ is the filtered signal. Normalisation is then performed to minimise inter-subject and inter-session variability as the feature scaling in learners should remain consistent. Discriminative features are then obtained after preprocessing with the aim of describing cognitive state changes in various domains. Features in the time domain represent statistical properties of the level of signal amplitude and temporal behaviour whereas frequency-domain features describe the distribution of signal energy to cognitively significant frequency bands. Specifically, the spectral energy of a particular frequency range is calculated as (2):

$$P_b = \int_{f_1}^{f_2} |X(f)|^2 df, \tag{2}$$

Where $X(f)$ denotes the Fourier transform of the preprocessed signal and $[f_1,f_2]$ corresponds to the frequency range associated with a given cognitive process. Besides the time and frequency features, the time frequency features are also obtained through the time frequency multiresolution analysis techniques like that of the wavelet transforms and this allows the non-stationary attributes that are usually exhibited by physiological signals to be well represented. Time, frequency-, and time-frequency-domain features are

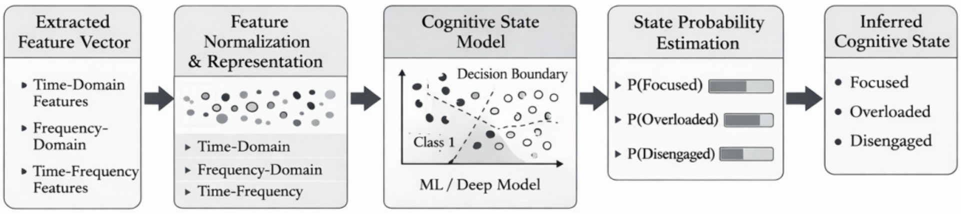

Fig. 2: Signal-feature-driven cognitive state inference pipeline.

extracted and concatenated to get a complete feature vector that is the input into the stage of modelling the cognitive state in the following section.**3.3 Cognitive State Modeling**

After signal preprocessing and feature extraction the resulting feature vectors are then applied to data-driven modelling to determine the cognitive state of the learner. The feature vectors of each feature are obtained by adding time-domain, frequency-domain and time-frequency-domain based features obtained on the preprocessed physiological signals as outlined in Section 3.2. This coherent image represents complementary statistical, spectral, and temporal properties of the cognitive activity and can be strongly used to distinguish between various cognitive states. Before training of a model, the feature vectors are put into fixed length representations that can be used by the supervised learning. In case of multimodal signals, information of varying modalities is time synchronised and integrated on feature level to produce a single input vector. This design decision provides that the cognitive state model works on context-aware and synchronised representations and still has computational efficiency.

Inference of the cognitive state is done through a classification model which gives the relation between the feature vectors of input to discrete cognitive states. The modelling framework is also deliberately made general and can be instantiated either on classical machine learning classifiers or deep learning structures, based on the specific application restraints. The architecture in the case of deep models can either be stacked fully connected layers, or a hybrid design that can represent nonlinear dependencies derivable in the feature space. The model aims at learning boundaries of decision that distinguish different cognitive states based on their signal properties. The cognitive state model is trained with the help of a supervised optimization problem, which reduces the error penalty of prediction of an incorrect state. The objective of the model optimization is defined based on the categorical cross-entropy loss, the expression of which is as follows (3):

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i), \qquad (3)$$

where N denotes the number of training samples, y_i represents the ground-truth cognitive state label, and $\hat{y}_i$ corresponds to the predicted probability of the correct cognitive state. The loss function helps in motivating accurate probabilistic estimation and aids the convergence to be stable throughout the training.

The pipeline of cognitive state inference, as shown in Figure 2, works by projecting normalised feature representations into the probabilistic estimates of every cognitive state. The model provides a probability distribution of the predetermined cognitive classes, which represents the confidence of one or the other possible state. This leaves the last cognitive state as the class that has been chosen with the greatest posterior probability. Cognitive states in this work are termed as discrete and intelligible affiliations that signify the mental condition of the learner throughout the learning process. In particular, there are three cognitive states, which include focused, overloaded, and disengaged. The reason why these states are chosen is cognitive interpretability and practical relevance in making adaptive learning decisions. The perceived cognitive state is the input in the dynamism in adaptive learning engine which adjusts the instructional strategies adaptively to the present cognitive condition of the learner.

Adaptive Decision Logic

The adaptive decision logic is the process involving the translation of the deduced cognitive state into the suitable learning system responses. The adaptive engine works with high-level control signals, and these are the discrete cognitive states generated by the cognitive state model, rather than working with raw physiological data or low-level features. This abstraction makes it easier to make decisions and makes it such that adaptation can be understood and computationally efficient. An adaptive action and cognitive state are determined in a deterministic manner. When the learner is concluded to be in full concentration, the system will keep at the same level of the instructional pace and the difficulty to facilitate the ongoing interaction. On the contrary, the overloaded state of cognition evokes adaptive mechanisms like a decrease in the complexity of the content, a decrease in the speed of presentation, or additional supportive feedback. Whenever a disengaged state is identified, the system will react by making the programme more interactive or giving the learner motivational feedback or even modifying the content delivery system to stimulate interest once again. This state/ behaviour mapping facilitates uniform and repeatable adaptation behaviour.

Feedback timing constraints are implemented in the decision logic as a way of stabilizing the system and preventing over or cutting back and forth adaptations. The value of cognitive state changes is considered across a set of predetermined time frames, and adaptive controllers only make changes when changes in state stand at least a set time parameter. this temporal regularisation process guarded against quick change in adaptation in response to momentary changes, or temporary noise, in the estimates of cognitive states. The response of the system is unidirectional with the adaptive decision-making being put on the e-learning environment, and the learner responses are manifested in the revised physiological signals. This closed-loop interaction, as shown in Figure 1, permits the system to self-correct through this interaction, without requiring any direct feedback dependencies in the modelling pipeline. Consequently, the adaptive decision logic is a lean and efficient control layer that mediates the cognitive state inference and personalised learning delivery.

Experimental Setup

The experimental environment will be configured in a way that guarantees reproducibility and objective assessment of the offered signal-based analysis of the cognitive state framework. The controlled e-learning data used in experiments consists of synchronised physiological signal recording with the learning event logs. Physiological data are divided into fixed length temporal windows in correspondence to the learning activities, and allowed the consistent mapping of cognitive state and instructional context. To evaluate the state of cognition of each segment, task conditions and observational criteria are attached which are used as ground truth to supervised model training and evaluation. The study was conducted with the help of a sample of participants having various academic backgrounds. The experimental protocol was a standardised procedure of all participants and involved various learning sessions where they were to cause the incidence of varying degrees of cognitive load and engagement. The protocol contained categorised educative material, interactive activities and evaluation tasks presented in a preconditioned order. To minimise the artefacts caused by movement, the participants were asked to make the least physical movements as possible when recording the data collected. All the processes were performed within the standard ethical guidelines and informed consent was taken before the participation.

Physiological measurements were also measured by non-invasive wearable devices. EEG-recording of neural activity was used to record cognition processes involving attention and workload, ECG and GSR recordings of autonomic responses associated with engagement and mental work. The samples of the signals were taken at modality-specific frequencies and all was synchronised to a single time stamping system so that there was timing alignment inter-modal. The preprocessing parameters, windows sizes, time sampling rates, and synchronisation were maintained among the subjects. Table 2 has a detailed description of signal acquisition parameters and experimental configuration.

Table 2. Experimental Configuration and Signal Acquisition Parameters

Parameter	Description / Value
Physiological signals	EEG, ECG, GSR
EEG channels	Multi-channel configuration
EEG sampling rate	250–512 Hz
ECG sampling rate	250 Hz
GSR sampling rate	50–100 Hz
Signal window length	Fixed-length temporal windows (e.g., 2–5 s)
Window overlap	50% overlap
Synchronization method	Unified timestamp-based alignment
Preprocessing steps	Band pass filtering, artifacts removal, normalization
Feature domains	Time-domain, frequency-domain, time-frequency
Cognitive state classes	Focused, Overloaded, Disengaged
Model type	Supervised ML / Deep learning classifier
Training-testing split	Subject-independent / k-fold cross-validation
Baseline methods	Interaction-driven models, signal-based classifiers
Evaluation metrics	Accuracy, Precision, Recall, F1-score
Number of experimental runs	Multiple runs with averaged results

In order to measure the efficiency of the suggested method, the effects on performance are contrasted with reference to baseline-based methods, based on traditional interaction-driven attributes, e.g., clickstream statistics, task performance indicators, and signal-based classifiers based on limited feature sets. Every model is trained and evaluated according to the same data partitions and evaluation setups in order to compare the models justly and without any bias. The evaluation of model performance is conducted using the commonly used classification metrics, such as accuracy, precision, recall, and F1-score that together give a thorough analysis of cognitive state recognition performance. Moreover, system-level metrics concerning adaptation learning performance, including duration of engagement and efficiency in performing tasks, are compared to understand the feasible effect that cognitive-state-based adaptation has on activity execution. The reported results are averaged across several runs in order to minimise the effect of random variation.

Performance Evaluation and Results.

Performance Classification Cognitive State.

The effectiveness of the suggested cognitive state modelling method is measured by the conventional classification criteria, such as accuracy, precision, recall, and F1-score. These measures represent an indicator of how well the model behaves as they provide a balance between accurate recovery of the estimations of the model and the correctness or incorrectness in predicting the results for each class, its dependence on the true cognitive states and the trade-off between precision and the recall. Against baseline methods of performance assessment, the effectiveness of inclusion of physiological signal-based features in the inference of cognitive state is quantified. The proposed signal-based model is always superior to both interaction-driven baseline and the conventional signal-based baseline in terms of all developed metrics (Figure 3). The interaction based model that uses indicators of learner behaviour and task performance only has the worst classification performance, and therefore reflects the poor capability of the model to entrap latent thinking processes. The addition of features of physiological signals provides a significant enhancement, as it can be seen in the signal-based baseline, which proved the value of biosignals information in the field of cognitive state recognition.

The model that is proposed has the best performance with the average F1-score of 85.7 as opposed to 76.9 of the signal-based and interaction-based model respectively. Accuracy, precision and recall show similar

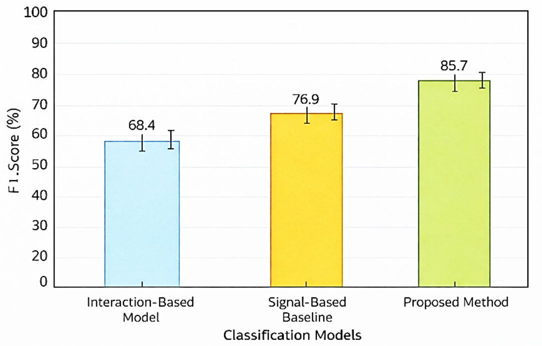

Fig. 3: Performance Comparison of Cognitive State Classification Models

trends thus showing that the proposed approach does not only enhance the overall accuracy of prediction but also a balanced trade-off between false positives and false negatives is observed between the cognitive state classes. Figure 3 also displays error bars, which again hint at the fact that the improvement in performance becomes evident in several runs of the experiment and cannot be explained by the chance error. On the whole, these findings substantiate the claim that when time-, frequency-, and time-frequency-domain physiological signal characteristics are combined as a single cognitive condition model, an important enhancement in classification performance is achieved compared to interaction-based and small-feature signal representations models.

Effect of Cognitive-Driven Adaptation.

In this sub section the effects of cognitive-state-driven adaptation on other learning results other than classification performance are considered in the aspect of system-level performance. The test factors involve learning efficiency, interaction, and system reaction latency as it evaluates the translation in the cognitive state inference into quantifiable learning process enhancements. The objective outcome measure used to determine learning efficiency is mainly post-test performance. Comparing learner outcomes in terms of post-test scores after being exposed to either cognitive-state-driven adaptive learning or the situation of non-adaptive learning as shown in Figure 4 one can say that learners in the former perform better than those in the situation with the latter. Adaptive system is a dynamically regulated method to deliver content according to the deducted cognitive conditions that allow learners to receive instructional content at the right pace and of the right difficulty. The given improvement demonstrates that real time-adaptation based on the cognitive state estimation leads to the more efficient knowledge acquisition.

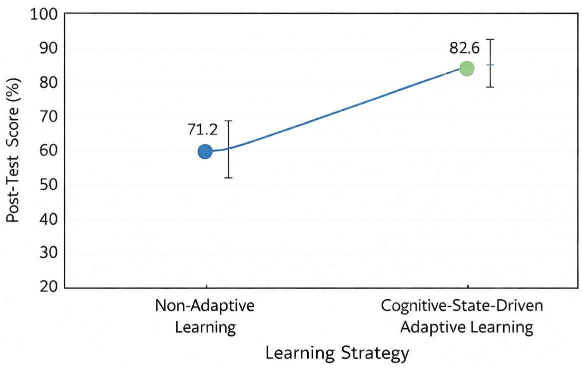

Fig. 4: Effect of adaptation on learning outcomes with figure mention

Engagement-related indicators are considered as well as learning outcomes so that to comprehend the behavioural implications of adaptation. There is prolonged interaction time and reduced occasions of sudden disengagement among learners who engage with the adaptive system, implying that learners are better at attention regulation. These patterns are found to agree with the adaptive decision logic, which injects in the supportive feedback or interactivity in circumstances of disengaged or overloaded states that are detected. Even though, interaction measures are not explicitly shown in Figure 4, they supplement the depicted increase in post-test performance by showing better quality of interaction between the learners and the system. Response latency which is the interval that exists between cognitive state detection and the execution of adaptive action is the measure of system responsiveness. The proposed scheme has a low response latency since adaptation logic is performed on output outputs of a high level cognitive state, as opposed to raw signal streams. This guarantees that the adaptive interventions can be provided in time without interfering the learning process. Early change in adapting and the uniform nature of decision logic can assist with the sustained behaviours in the system throughout the learning sessions. In general, the findings presented in Figure 4 allow confirming that cognitive-state-based adaptation provides actual improvements at the level of learning outcomes. These results, along with the effects on classification performance that are presented in Section 5.1, indicate that the suggested framework does not only enhance the accuracy of cognitive state recognition but is also able to transfer these gains into any form of real improvement in adaptive e-learning effectiveness.

Discussion

Findings reported in this work indicate that incorporating physiological signal assessment and adaptive learning on the system level can bring quantifiable improvements that are both beneficial at the system level and in the modelling level. The suggested framework demonstrates standard gains in the cognitive state classification results over interaction-driven and limited-feature signal-based baselines, indicating that multimodal physiological signals acquire latent cognitive dynamics that cannot be assessed by behaviour data alone. The increase in the F1-score and other measures that follow shows that the combination of time-, frequency-, and time-frequency-domain representations allows more resilient discrimination between focused, overloaded, and disengaged state cognitions. In addition to the accuracy in the classification, the effects of cognitive-state-based adaptation on learning outcomes underscore the fact that precise cognitive inferences can be important in practise. Figure 4 indicates that adaptive learning that involves inferred cognitive states results in increased post-test performance over non-adaptive learning. It implies that learning efficiency can be enhanced through personalization based on real-time cognitive feedback to synchronise the pace of instruction and challenge with the current state of the mind in the learner. Notably, these enhancements are realised without the need to have the complicated pedagogical regulations, but rather with lightweight and elucidable decision logic. The trends observed in the area of engagement confirm the efficiency of the suggested method as well. Fewer incidences of disengagement and longer-lasting periods of interaction suggest that adaptative interventions if administered in time assist in stabilising learner attention in situations of cognitively strenuous undertaking. Further, the fact that the adaptive engine has a very short response latency is evidence that functioning on the cognitive state level, as opposed to working on raw signals, offers a convenient solution to the problem of integrating responsiveness and computational efficiency. This design selection is specifically applicable to resource-constrained or real-time e-learning systems. Although these were positive results, some constraints are to be noted. The experimental assessment is made under the conditions of control of learning, and the tendency of the findings to be generalised to large-scale and open-ended learning platforms is also a subject of further study. In addition, the labels of cognitive states are based on task conditions and observation parameters, and they may be insufficient to reveal the complexity of personal cognitive experiences. Adaptation fidelity may be further improved by using more finer or continuous representations of cognitive states. All in all, the discussion points out that the main contribution of this work is not only the better ability to recognise the state of sounds, but it also shows the definite way of how signal-based inference can lead to tangible learning benefits. The results indicate that cognitive-state-conscious adaptation is one of the bright paths of the development of intelligent, human-oriented e-learning systems becoming technically sound and practically efficient.

Conclusion and Future Work

The paper introduced a signal based cognitive state analysis framework applied to adaptive e-learning environments which combines the processing of physiological signals, modelling the state of cognition and adaptive decision logic realised in real-time. The proposed approach will allow underlining the appropriate inference of learner cognitive states with the multimodal physiological signals and featuring representations in time, frequency, and time-frequency domain, and facilitate dynamic personalization of the learning content. The experimental findings indicate that the suggested model can be used to attain better cognitive state classification scores than interaction-based and traditional signal-based baselines. Significantly more importantly, the combination of cognitive-state-induced adaptation results in a quantifiable increase in the outcome of learning such as the increase in post-test performance and learning efficiency. The results validated that providing correct inference of the state of cognition can be practically introduced to tangible system advantages in a lightweight and interpretable adaptive decision mechanism. The framework designed is in general and scalable fashion. Its modular structure enables adaptation of the cognitive state model and adaptive logic to other learning situations, signal modalities as well as computational limitations. The high-level representations of cognitive state are also used which makes adaptation to the high-latency, thus making the practise appropriate in the real-time and resource-bound e-learning systems. Future directions will be endeavoured towards detection of the framework to more varied and varied learning settings like longitudinal research with diversified learner's communities. Other signal modalities, and considering continuous/personalised representations of cognitive states, can be further incorporated to achieve a larger adaptation precision. Future studies can also examine how to incorporate more elaborate learning procedures, e.g., reinforcement learning or self-supervised modelling, in order to allow more autonomous and situation-specific adaptation policies. Lastly, it will be necessary to measure the framework in deployed educational systems at full scale to measure the impact of long-term learning and system stability under the conditions of the real-world environment.

References

1. Alarcão, S. M., & Fonseca, M. J. (2017). Emotions recognition using EEG signals: A survey. *IEEE Transactions on Affective Computing, 10*(3), 374-393. https://doi.org/10.1109/TAFFC.2017.2714671
2. D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*(2), 145-157. https://doi.org/10.1016/j.learninstruc.2011.10.001
3. Koelstra, S., Mühl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., Patras, I. (2011). DEAP: A database for emotion analysis using physiological signals. *IEEE Transactions on Affective Computing, 3*(1), 18-31. https://doi.org/10.1109/T-AFFC.2011.15
4. Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. (2018). EEGNet: A compact convolutional neural network for EEG-based brain-computer interfaces. *Journal of Neural Engineering, 15*(5), 056013. https://doi.org/10.1088/1741-2552/aace8c
5. Siemens, G., & Baker, R. S. D. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 252-254). ACM. https://doi.org/10.1145/2330601.2330661
6. Soleymani, M., Lichtenauer, J., Pun, T., & Pantic, M. (2011). A multimodal database for affect recognition and implicit tagging. *IEEE Transactions on Affective Computing, 3*(1), 42-55. https://doi.org/10.1109/T-AFFC.2011.25
7. Van Erp, J., Lotte, F., & Tangermann, M. (2012). Brain-computer interfaces: Beyond medical applications. *Computer, 45*(4), 26-34.https://doi.org/10.1109/MC.2012.107
8. Villarejo, M. V., Zapirain, B. G., & Zorrilla, A. M. (2012). A stress sensor based on galvanic skin response (GSR) controlled by ZigBee. *Sensors, 12*(5), 6075-6101. https://doi.org/10.3390/s120506075
9. Zander, T. O., & Kothe, C. (2011). Towards passive brain-computer interfaces: Applying brain-computer interface technology to human-machine systems in general. *Journal of Neural Engineering, 8*(2), 025005. https://doi.org/10.1088/1741-2560/8/2/025005
10. Zheng, W.-L., & Lu, B.-L. (2015). Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. *IEEE Transactions on Autonomous Mental Development, 7*(3), 162-175. https://doi.org/10.1109/TAMD.2015.2431497
11. Jin, K., Rubio-Solis, A., Naik, R., Leff, D., Kinross, J., & Mylonas, G. (2025). Human-centric cognitive state recognition using physiological signals: A systematic review of machine learning strategies across application domains. *Sensors, 25*(13), 4207. https://doi.org/10.3390/s25134207
12. Baker, R. S. J. d., & Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning analytics* (pp. 61-75). Springer.https://doi.org/10.1007/978-1-4614-3305-7_4