Aggregating Attention, Emotion, and Cognition Load as Basis for Developing a Rule-based Pedagogy for Online Learner

Anna Liza A. Ramos[1] and Melvin A. Ballera[2]

[1]Graduate School Student, Technological Institute of the Philippines, Manila, Philippines, malramos@tip.edu.ph
[2]Graduate School Faculty, Technological Institute of the Philippines, Manila, Philippines, melvin.ballera@tip.edu.ph

Abstract

The e-learning system offers an opportunity for educational strategists to monitor the learners' status and improve the teaching-learning outcomes. The study aims to analyze the electroencephalogram (EEG) signal of the learners' attention, emotion, and cognition as determining factors to recommend an appropriate learning pedagogy for every learner. The study analyzed 5,400 data signal datasets with the application of different algorithms to optimize and label the signal classification categories. The data signal components were aggregated as inputs to the regression model. Its resulting p-value determined the prioritization which significantly impacted the learners' learning process. Based on the initial simulation of signal analysis, the study recommends an individualized rule-based pedagogy for each learner, incorporating the EEG instrument to collect the affective and cognitive attributes that can help the learners to adjust better and follow their learning process with minimal supervision of the educational strategist. Likewise, implementing this study in the current e-learning system would provide tremendous learning benefits and improvements in the teaching-learning process.

Keywords: *e-learning, electroencephalogram signal, aggregated function, regression model, rule-based pedagogy*

Introduction

The unprecedented impacts brought about by the COVID-19 pandemic compelled educational institutions to transition to an online learning environment through various learning applications (Ali et al., 2020). Therefore, academic strategists were forced to develop well-designed courses that balance theoretical and practical teachings to cope with the new virtual setting (Kaur et al., 2020). Learners' engagement and motivation must be established more than ever to improve their learning process and embrace technological innovation as it will help them gain competitive advantage (Sun & Chen, 2016) and cultivate their cognitive, attention, and emotional capacities towards learning (El Kerdawy et al., 2020). In fact, the relationship between these components has been significantly supported in several studies, where attention and cognition were found to have a significant connection in ensuring learners' achievement (Braude & Dwarika, 2020; Ellah et al., 2019; Peng & Kievit, 2020). Moreover, Hasher's (2010) study showed a positive correlation between emotion and cognition in terms of e-learning success and suggested that emotion is a significant element in improving learners' attention spans and teaching-learning outcomes (Butt & Igbal, 2011; Huang et al., 2020; Qin et al., 2020).

As various studies delved into attention, emotion, and cognition to investigate the learning process, a study conducted by Huang et al. (2020) calculated the cognitive status based on attention, measuring the learner's ability and performance scores (Zhang et al., 2020). Eye-gaze was also used to determine the learners' attention (Costecu et al., 2019). Accordingly, Chisari et al. (2020) examined the said component through visual ability, whereas Yuan and Yang (2020) and Ciu et al., (2019) assessed attention based on user preferences. Further, Hlas et al. (2019) also studied other possible factors determining whether attention is based on working memory. Aside from attentiveness, emotion is also considered to be effective in the learning process, particularly in assessing student comprehension (Jia et al., 2021). In fact, it has been found that it also serves as a source of student motivation (Valverde-Berrosco et al., 2020), with the learners' body posture being closely linked (Revadakar et al., 2020). Likewise, facial expressions and electroencephalogram (EEG) signals are now being used to study the learners' emotions (Li et al., 2019). More studies were conducted to look into the field of emotion which also include a gender-based comparative analysis of emotions (Dores et al., 2020), emotional experiences encountered during e-learning sessions (Pal et al., 2020), and emotions assessed through using different types of images (Moroto et al., 2020). On the other hand, the cognition and cognitive abilities of the learners were found to be measured through test administration (Liu et al., 2015). Consequently, Paas and Merrienboer (2020) stated that assigning extremely difficult learning tasks distributes cognitive load among learners, and it could be best assessed through the task difficulty and performance scores (Hettiaracchi et al., 2018).

Based on the reviews conducted, most of the studies are descriptive in nature as some only focused on psychological aspects by assessing memory load, and there were only a few that utilized technologies to assess attention, emotion, and cognition among learners due to research limitations in adopting artificial intelligence (AI) to both pedagogical and psychological aspects (Zawacki et al., 2019). As Homes et al. (2019) asserted that academic integration of AI is limited, which then explains why only a minority of educators know the benefits of incorporating AI into the teaching-learning process (Linder, 2019). These factors greatly influenced this study's motivation to employ AI via an EEG tool, as only limited research had used the said technique (William et al., 2020). Several recommendations on using an EEG tool on assessing the cognitive load (Ahmad et al., 2020) and investigating changes on students' attention (Huang et al., 2020) were also suggested to understand the teaching-learning process better.

Grounded on integrating AI in the academic setup, this study would also like to investigate the issues and challenges in e-learning that concern the learner's attention, emotion, cognition load, and skills to see how they affect the e-learning system. The first component specifically tackles the learners' attention issues for it is noted that their attention in an e-learning environment is heavily distracted by complex learning content presentations, and learners cannot relate the importance of the stated information to the learning objectives. The visual display also affects their attention (Amadioha, 2019; Bradbury, 2016; Ghorbani et al., 2019; Tremolada et al., 2019;), and findings revealed that the best way to increase a learner's attention is to provide cognitive activities through problem-solving and thinking (Ellah et al., 2019). Alongside attention, the learners' emotions come as the second component. A study by Hewson (2018) mentioned that learners who engage in e-learning were mostly frustrated. Thus, one of the most prevalent emotions detected in e-learning is anxiety due to excessive boredom towards task irrelevancy, which was also found to be detrimental to student academic performance. Hence, positive emotions were detached in e-learning materials with less critical topics and irrelevant learning contents (Hasher, 2010). Another cited issue in e-learning is that learners get confused about the faulty learning materials, significantly affecting understanding and learning (Lodge et al., 2018). In terms of providing activities, studies revealed that learners also experience test anxiety in the e-learning set-up. Likewise, the activities in the new e-learning environment may pose positive emotions for learners to perform better (Adesolo & Yi, 2020).

On the contrary, negative emotions were observed when the given task was complex (Shao et al., 2019) leading to another challenge in areas of facilitating all the learning materials while receiving negative emotions in a short period (Li et al., 2020). Based on the reported cases in e-learning, the general emotions that the learners feel include enjoyment, hope, pride, relief, anger, anxiety, shame, hopelessness, and boredom. The third component is learner cognition, where several studies investigated if the quality of e-learning materials provides poor instructions that suggest lower performance levels (Costley, 2019). It has also been found that learning activities with multiple information sources reduce cognitive load (Winn et al., 2019), making the learners' intrinsic cognitive load and their ability to receive and process information be limited. In contrast to this, the learners' extraneous cognitive load understands the simulation lecture's information when they have a low mental load level (Permana et al., 2019). Furthermore, as stated in the systematic review of Hwang et al. (2021), most of the studies on AI in education from 1996 to 2019 measured the students' actual learning performances, and only few have considered the students' higher-order skills. However, despite being so invested in the students’ skills, none of the studies delved into the students' cognitive load.

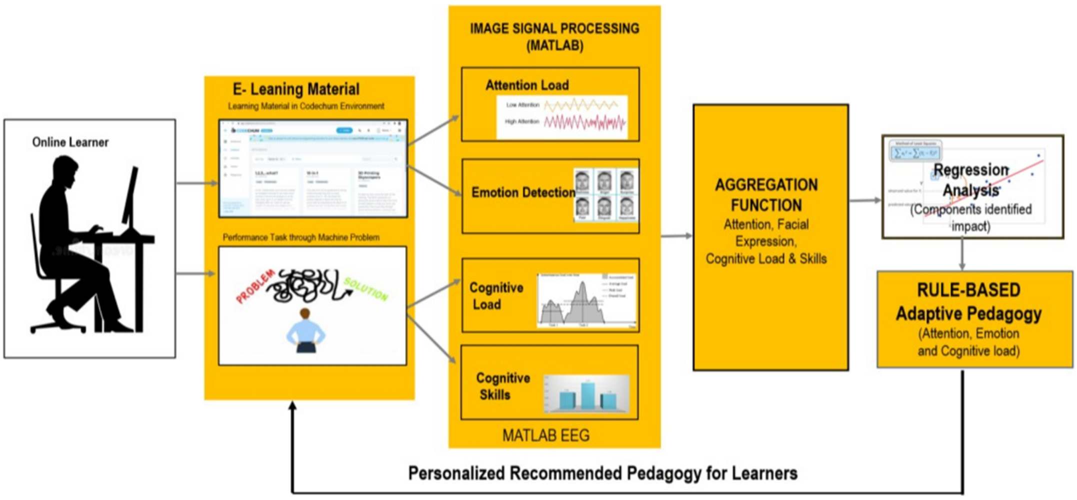
Therefore, this study looked closely at these critical components, including the valuable tools for assessing the students' learning process to arrive at an in-depth assessment of academic competence and valuable inputs for educational strategists. The results from this study would also allow the implementation of more appropriate learning pedagogies through improving the teaching-learning outcomes, which concerns the relevance and usefulness of learning content and the overall strategies being used in learning. Additionally, as this study considered using an EEG tool to conduct a more comprehensive diagnostic assessment of the learner's mental state, including their ability to absorb, process, and manage the received information, it would enable real-time assessments in the e-learning environment and permit generating relevant data that could be utilized as a strong basis for stakeholders’ decision-making.

Objectives

The overarching objective of the study was to establish aggregated functions for attention, emotion, and cognition load as bases to develop a rule-based pedagogy approach for online learners.

Figure 1

Conceptual Framework of an Aggregated Function that serves as a Basis for Rule-Based Adaptive Pedagogy



Each learner performs two different tasks. The learners are instructed to wear the EEG tool while reading the e-learning material to capture and record both of their attention and emotion, which would then lead to performing the machine problem activities to capture and record the learner's cognitive load and skills. The data would be collected and extracted for further analysis through using algorithms and mathematical functions. The final data signal of the learner's attention, emotion, and cognition load values would be aggregated as input to the regression model. The created model would identify which among the three variables/components show the significant impact that could serve as a basis for selecting adaptive pedagogy to improve the existing e-learning system.

Review of Related Literatures

As presented in the introduction, the variables in this study are the identified critical components based on numerous existing studies that also delved into assessing the status of learners' learning process. Attention, emotion, and cognition emerged as the most effective and significant domains of the learners, based on the variety of approaches and methodologies used. In this study, these three (3) components were mainly employed to collect comprehensive data that educational strategists may consider, to improve the teaching-learning process.

Attention

A learner's attention is a factor in attaining academic achievement and personal and social development (Braude & Dwarika, 2020). Several characteristics that define and affect attention include having the individual capacity for information processing, attentiveness, inattention, divided attention, flexibility, and sustained attention (Tremolada et al., 2019). It varies according to individual preferences and circumstances, which were also proved by additional studies that examined attention on a cognitive level (e.g., Huang et al., 2020). As Costescu et al. (2020) investigated eye-gaze in measuring attention, some studies assessed attention through performance scores (Zhang et al., 2019), and learning working memory (Hlas et al., 2019; Yuan & Yang, 2020). Observing learners' attention value to various learning materials (Huang et al., 2020) and assessing attention in terms of individual differences in information processing (Liu et al., 2019) were indicated as useful inputs for further investigation. Furthermore, Zhang et al. (2020) emphasized that it is likewise necessary to measure attention in terms of performance tasks.

Emotion

Facial expression is a highly effective method in deciphering social interactions. Emotions are used to demonstrate student motivation (Valverde-Berrocoso et al., 2020) as it broadens the perspective of the learners (Shao et al., 2019). Numerous studies, such as Moroto et al. (2020), have also examined the emotional component considering the emotions through visual responses to images. Body posture was also found effective in assessing learners' emotions during e-learning lessons (Revadekar et al., 2020). Hence, Li et al. (2019) and El Kerdawy et al. (2020) studied the fusion of EEG and facial expressions to understand the learning process better. Despite having intensive studies on gender-specific emotions (Dores et al., 2020), and assessing emotions during e-learning sessions through Learning Management Systems (LMS) data (Pat et al., 2020), the emotion component has been discovered to have no effect on either attention or cognitive abilities (Deng & Ren, 2020; El Kerdawy et al., 2020).

Cognition

A recent study conducted by Peng and Kievit (2020), established that the students' cognitive abilities directly affect their academic success. Similarly, innovative instructional strategies promote critical and analytical thinking (Chisari et al., 2020) as cognitive exercises (Ratniece, 2019) promote higher-order thinking and problem-solving abilities. It also demonstrates (Tachie, 2019) practical and physical abilities. Songkram et al. (2014) even emphasized that cognition is heavily based on the learner's scientific thinking process and systematic abilities.

Alongside investigating the learners' cognitive abilities, studies on assessing it were also conducted, where test assessments (Liu, 2015) and learners' performance were found to be relevant (Hettiarchchi et al., 2018). Numerical ability, logical reasoning ability, and perceptual speed (Kalpanedi, 2019) were also considered to be significant. Consequently, a study by Joe-Hee et al. (2019) established a relationship between various workloads where the learners' cognitive load may be assessed (Ahmad et al., 2020; Farisha et al., 2019). To better understand the learners' cognitive potentials, studies recommend more inputs to investigate cognitive capacities based on brain signals (Ahmad et al., 2020) and consider additional samples with extraneous variables (Ahmad et al., 2020; Joo-Hee et al., 2018).

Methodology

Research Design

The study used a quantitative approach and an experimental design to ascertain the relationship between the variables examined, specifically implying attention, emotion, and cognition as independent variables based on EEG signal. The performance scores from the machine problems serve as the dependent variable. The regression result will serve as input to recommend appropriate teaching pedagogy to improve e-learning.

Respondents

Learner Respondents

The study applied the proportionate stratified random sampling technique that follows the formula: nh = (Nh / N) * n, where the selected respondents have a brief background in C++ programming as a pre-requisite of the study. The respondents were composed of ten (10) males and ten (10) females.

Validator Respondents

The study used a purposive sampling technique in selecting the respondents to perform ranking on their priority pedagogy, based on the learner's level of attention, emotion, and cognition. The criteria among respondents included having a Master's or Doctoral degree in education and at least five years of teaching experience.

Data Gathering Procedure

The researchers intended to develop an e-learning material covering the iterative structures and arrays using C++ programming language, including learning objectives, salient information, simulation, sample code, flowchart, pseudocode, and machine problems. Before facilitating the material, experts evaluated the learning material and the machine problem to ensure its alignment and relevance to the identified learning objectives.

Before the Actual Conduct of the Experiment

Each learner took a pre-test on C++ Computer Programming, consisting of thirty (30) multiple-choice questions ranging from easy, average, and difficult to check on the learner's logical thinking abilities without using an EEG. The activity's concept and content were set to be similar, but the machine problems, on the other hand, were constructed differently in a way that it could investigate the learners' performance consistency. The post-test would then involve learners' wearing the EEG tool while completing the machine problem. Hence, the learners' pre-test and post-test results were compared.

During the Actual Conduct of the Experiment

The subjects were placed in a controlled environment to avoid disruption from environmental factors. The Emotiv EPOC+14 Channel Mobile Encephalogram (EEG) tool recorded the learners' attention, cognition, and emotion every 20 seconds. The subjects performed the eyes-closed and eyes-opened practice to establish the learner's relaxation mode before collecting the data on their memory working before reading and performing the tasks. As a result, the study collected a total of 5,400 datasets.

Table 1

Total number of Datasets

Subject	No of Subjects	Attention	Emotion	Cognition	Total datasets
Female	10	90	90	90	2,700
Male	10	90	90	90	2,700
				Over-all total	5,400

Analysis

As shown in Figure 2, the data collected were extracted and processed using algorithms. Each recorded signal for every learner was aggregated using a weighted mean to arrive at the final value of the learner's attention load (AI), emotion load (EL), and cognitive load (CL) (see Equations 1, 2, 3). These three (3) variables served as the independent variables, and the performance scores served as the dependent variable. The p-value result of the regression was then used to determine the rule-based approach that affected the pedagogical strategy of the learner. Hence, the generated results from this study could be used as a valuable tool for the educational strategists to arrive at the best-recommended pedagogy. This will also provide information to educational strategists to improve the learning materials as the attention and emotion of the learners are investigated and possibly redesign or revisit the machine problem given to the learners as the cognitive load is investigated.

Figure 2

EEG Signal Extraction and Processing

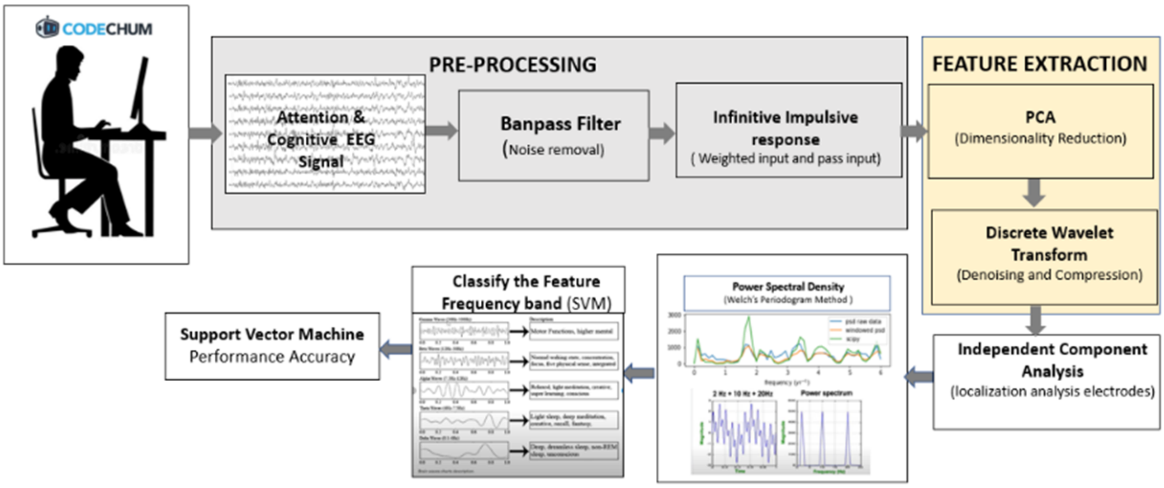


Figure 2 shows the method of processing the signals extracted from the BCI Software. The study utilized the MATLAB EEG tool to process the signals and arrive at the final value of the EEG signal through implementing algorithms such as Bandpass filter and infinite impulse response (IIR) filter to remove the noise. The Principal Component Analysis (PCA) was also used for signal feature extraction and dimension reduction. The discrete wavelet transforms also assisted in looking into the frequency signal. Moreover, the Independent Component Analysis (ICA) with a runica method to isolate the signal source was utilized. The autocorrelation function estimated the Fourier transform signal's power spectrum, and Welch's Periodogram method computed the Fourier transforms to better determine the brain signal's oscillatory mode levels.

Table 2

Oscillation Mode

Type of Waves	Frequency	Classification
Gamma Waves	32Hz-63Hz	Higher Mental Load
Beta Waves	16Hz-32Hz	Normal Mental Load
Alpha Waves	8Hz-12Hz	Low Mental Load

Aggregated Function

The data collected were extracted and processed using algorithms. Each recorded signal for every learner was aggregated as shown in the function, by using a weighted mean to arrive at the final value of the learner's attention, emotion, and cognitive load where it combined three variables as expressed:

$$AI/CL/E = \sum_{i=0}^{n} \frac{s1 + s2 + s3 + s4 \ldots}{n}$$

Where: AI = Attention load CL = cognitive load
E= emotions s = brain signal frequency data
n = number of collected brain signal frequency data

For the emotion data, the recorded data were labeled based on the six basic emotions: happy, sad, neutral, disgust, anger, and surprise, which were computed (see Equation 1).

$$te = \left(\frac{secm}{sec}\right) x \ tnms$$

Where: secm = equivalent of sec; sec = actual equivalent of sec; tnms = total number of minutes; te = total number of emotions

To establish the emotion combination pattern, the study applied percentage distributions to determine the emotion category (see Equation 2).

$$pve = re \ x \ te$$

Where: pve = percentage value per Emotion; re = specific recorded Emotion; te = total number of emotions

The recorded higher frequency values served as inputs to the combinatorial analysis adopted in the study of Mukhopadhyay et al. (2020), which was reflected (see Equation 3).

$$c = (n + s + sd)$$

Where: c = confusion; n = neutral; sr = surprise; sd = sad

$$s = (h + n)$$

Where: s = satisfaction; h = happy; n = neutral

$$d = (n + sd)$$

Where: d = dissatisfaction; n = neutral; sd = sad

$$f = (s + an + n)$$

Where: f = frustrated; s = sad; an = angry; n = neutral

Regression Model

The aggregated attention, emotion, and cognitive load values were the independent variables, with the learners' performance score as the dependent variable. The regression results provided empirical outcomes based on the obtained p-values with a 0.05 level of confidence. This p-value served as a basis to determine the variables' significance (see Equation 4).

$$\hat{Y} = \boldsymbol{b_0 + b_1 Al_1 + b_2 Fe_2 + b_3 Cl_3 + \cdots b_p X_p}$$

Where:

y = predicted or expected value of the dependent variable (performance score)
b_0 = value of Y when all independent variables are equal to zero
$Al_1 Fe_2 Cl_3$ = independent variables or predictors that consist of attention, emotion, and cognitive load
b_1 = through b_p are the estimated regression coefficients

Rule-Based Pedagogy

The study established a survey of the three significant components: attention, emotion, and cognition to determine the recommended pedagogy. The experts in the education field ranked these components according to the mental load types such as high, normal, and low load using a scale of 1 to 5 using the design rule-based below.

Ethical Considerations

Prior to the simulation, the researchers obtained consent to process, share, and protect all relevant information that was solely collected for research purposes only. In accordance with the Data Privacy Act, the purpose of the study was also clearly articulated among the respondents. Foremost, the study ensured that proper safeguards were in place while conducting experiments and recording the brain signals of the respondents.

Results and Discussions

This study presented the simulated analysis result based on the data signal classification category, classified as High Mental Load, Normal Mental Load, and Low Mental Load. Below is the expert judgment of mapping the prioritization of the best relevant pedagogy for specific online learners.

Table 3

Mapping of Recommended Pedagogy based on Cognitive Load

LOAD TYPE	RECOMMENDED PEDAGOGY BASED ON COGNITIVE LOAD CLASSSIFICATION				
High Mental Load	**5th Priority**	**4th Priority**	**3rd Priority**	**2nd Priority**	**1st Priority**
	HL>=33 && HL<=38 Hz	HL>=39 && HL<=44	HL>= 45 && HL<=50	HL>=51&& HL<=56	HL>=57 && HL <=63
	Reflective	Collaborative	Constructivist	Inquiry	Integrative
Normal Mental Load	**5th Priority**	**4th Priority**	**3rd Priority**	**2nd Priority**	**1st Priority**
	NL>=16 && NM<=18 Hz	NL>=19&& NL<=21	NL>=22&& NL<=24	NL>=25&& NL<=27	NL>=28 && NL <=32
	Collaborative	Integrative	Reflective	Constructivist	Inquiry
Low Mental Lod	**1st Priority**	**2nd Priority**	**3rd Priority**	**4th Priority**	**5th Priority**
	LL>=1 && LL<=2 Hz	LL>=2&& LL<=5	LL>=6&& LL<=8	LL>=9&& LL<=10	LL>=11&& LL<=15
	Integrative	Reflective	Collaborative	Inquiry	Constructivist

Table 3 depicts the recommended pedagogy based on the cognitive load of the learners. The categorization is based on signal oscillation classification through the scaling method to set up the range per priority.

Criteria No.1: High Cognitive Load

IF Cognitive Load >=57 && <=63 THEN recommend 1st Priority Pedagogy
ELSEIF Cognitive Load >=51 && <=56 THEN recommend 2nd Priority Pedagogy
ELSEIF Cognitive Load >=45 && <=50 THEN recommend 3rd Priority Pedagogy
ELSEIF Cognitive Load >=39 && <=44 THEN recommend 4th Priority Pedagogy
ELSE Cognitive Load >=33 && <=38 THEN recommend 5th Priority Pedagogy

Criteria No.2: Normal Cognitive Load

IF Cognitive Load >=28 && <=32 THEN recommend 1st Priority Pedagogy
ELSEIF Cognitive Load >=25 && <=27 THEN recommend 2nd Priority Pedagogy
ELSEIF Cognitive Load >=22 && <=24 THEN recommend 3rd Priority Pedagogy
ELSEIF Cognitive Load >=19 && <=21 THEN recommend 4th Priority Pedagogy
ELSE Cognitive Load >=16 && <=18 THEN recommend 5th Priority Pedagogy

Criteria No.3: Low Cognitive Load

IF Cognitive Load >=1 && <=2THEN recommend 1st Priority Pedagogy
ELSEIF Cognitive Load >=2 && <=5 THEN recommend 2nd
Priority Pedagogy
ELSEIF Cognitive Load >=6 && <=8 THEN recommend 3rd Priority Pedagogy
ELSEIF Cognitive Load >=9 && <=10 THEN recommend 4th Priority Pedagogy
ELSE Cognitive Load >=11 && <=15 THEN recommend 5th Priority Pedagogy

Table 4

Mapping of Recommended Pedagogy based on Attention Load

LOAD TYPE	RECOMMENDED PEDAGOGY BASED ON ATTENTION LOAD CLASSSIFICATION				
High Attention Load	5th Priority	4th Priority	3rd Priority	2nd Priority	1st Priority
	HL>=33 && HL<=38 Hz	HL>=39 && HL<=44	HL>= 45 && HL<=50	HL>=51&& HL<=56	HL>=57 && HL <=63
	Collaborative	Integrative	Reflective	Constructivist	Inquiry
Normal Attention Load	5th Priority	4th Priority	3rd Priority	2nd Priority	1st Priority
	NL>=16 && N M<=18 Hz	NL>=19&& NL<=21	NL>=22&& NL<=24	NL>=25&& NL<=27	NL>=28 && NL <=32
	Collaborative	Integrative	Reflective	Integrative	Inquiry
Low Attention Load	1st Priority	2nd Priority	3rd Priority	4th Priority	5th Priority
	LL>=1 && LL<=2 Hz	LL>=2&& LL<=5	LL>=6&& LL<=8	LL>=9&& LL<=10	LL>=11&& LL<=15
	Integrative	Reflective	Collaborative	Inquiry	Constructivist

The mapping of recommended pedagogies dependent on the level of learners' attention load is shown in Table 4. The categorization is based on the signal's oscillation classification, with the range per priority set up using the scaling method:

Criteria No.1: High Attention Load

IF Attention Load >=57 && <=63 THEN recommend 1st Priority Pedagogy
ELSEIF Attention Load >=51 && <=56 THEN recommend 2nd Priority Pedagogy
ELSEIF Attention Load >=45 && <=50 THEN recommend 3rd Priority Pedagogy
ELSEIF Attention Load >=39 && <=44 THEN recommend 4th Priority Pedagogy
ELSE Attention Load >=33 && <=38 THEN recommend 5th Priority Pedagogy

Criteria No.2: Normal Attention Load

IF Attention Load >=28 && <=32 THEN recommend 1st Priority Pedagogy
ELSEIF Attention Load >=25 && <=27 THEN recommend 2nd Priority Pedagogy
ELSEIF Attention Load >=22 && <=24 THEN recommend 3rd Priority Pedagogy
ELSEIF Attention Load >=19 && <=21 THEN recommend 4th Priority Pedagogy
ELSE Attention Load >=16 && <=18 THEN recommend 5th Priority Pedagogy

Criteria No.3: Low Attention Load

IF Attention Load >=1 && <=2THEN recommend 1st Priority Pedagogy
ELSEIF Attention Load >=2 && <=5 THEN recommend 2nd Priority Pedagogy
ELSEIF Attention Load >=6 && <=8 THEN recommend 3rd Priority Pedagogy
ELSEIF Attention Load >=9 && <=10 THEN recommend 4th Priority Pedagogy
ELSE Attention Load >=11 && <=15 THEN recommend 5th Priority Pedagogy

Table 5

Mapping of Recommended Pedagogy based on Emotion

EMOTION	RECOMMENDED PEDAGOGY BASED ON EMOTION CLASSSIFICATION				
Satisfaction	5th Priority	4th Priority	3rd Priority	2nd Priority	1st Priority
	HL>=33 && HL<=38 Hz	HL>=39 && HL<=44	HL>= 45 && HL<=50	HL>=51&& HL<=56	HL>=57 && HL <=63
	Collaborative	Reflective	Constructivist	Inquiry	Integrative
Confusion	5th Priority	4th Priority	3rd Priority	2nd Priority	1st Priority
	NL>=16 && NM<=18 Hz	NL>=19&& NL<=21	NL>=22&& NL<=24	NL>=25&& NL<=27	NL>=28 && NL <=32
	Constructivist	Inquiry	Reflective	Integrative	Collaborative
Dissatisfaction	1st Priority	2nd Priority	3rd Priority	4th Priority	5th Priority
	LL>=1 && LL<=2 Hz	LL>=2&& LL<=5	LL>=6&& LL<=8	LL>=9&& LL<=10	LL>=11&& LL<=15
	Collaborative	Integrative	Reflective	Inquiry	Constructivist
Frustration	1st Priority	2nd Priority	3rd Priority	4th Priority	5th Priority
	LL>=1 && LL<=2 Hz	LL>=2&& LL<=5	LL>=6&& LL<=8	LL>=9&& LL<=10	LL>=11&& LL<=15
	Collaborative	Integrative	Reflective	Inquiry	Constructivist

The mapping of recommended pedagogies based on the level of learners' emotion load signal is shown in Table 5. Negative Emotions (Frustration and Dissatisfaction), Normal Emotions (Confusion), and Positive Emotions (Excitement and Joy) were the three types of emotions that correlate to (Satisfaction). According to Fredrickson (2011), low emotion denotes disengagement, while high emotion denotes engagement or satisfaction. The suggested rule- based approaches are as follows:

Criteria No.1: Positive Emotion (Satisfaction)

IF Positive Emotion >=57 && <=63 THEN recommend 1st Priority Pedagogy
ELSEIF Positive Emotion >=51 && <=56 THEN recommend 2nd Priority Pedagogy
ELSEIF Positive Emotion >=45 && <=50 THEN recommend 3rd Priority Pedagogy
ELSEIF Positive Emotion >=39 && <=44 THEN recommend 4th Priority Pedagogy
ELSE Negative Emotion >=33 && <=38 THEN recommend 5th Priority Pedagogy

Criteria No.2: Neutral Emotion (Confusion)

IF Neutral Emotion >=28 && <=32 THEN recommend 1st Priority Pedagogy
ELSEIF Neutral Emotion >=25 && <=27 THEN recommend 2nd Priority Pedagogy
ELSEIF Neutral Emotion >=22 && <=24 THEN recommend 3rd Priority Pedagogy
ELSEIF Neutral Emotion >=19 && <=21 THEN recommend 4th Priority Pedagogy
ELSE Neutral Emotion >=16 && <=18 THEN recommend 5th Priority Pedagogy

Criteria No.3: Negative Emotion (Frustration & Dissatisfaction)

IF Negative Emotion >=1 && <=2THEN recommend 1st Priority Pedagogy
ELSEIF Negative Emotion >=2 && <=5 THEN recommend 2nd Priority Pedagogy
ELSEIF Negative Emotion >=6 && <=8 THEN recommend 3rd Priority Pedagogy
ELSEIF Negative Emotion >=9 && <=10 THEN recommend 4th Priority Pedagogy
ELSE Negative Emotion >=11 && <=15 THEN recommend 5th Priority Pedagogy

Conclusions and Recommendations

It is critical to monitor the learner's mental state throughout the learning process as it reveals how they process, analyze, and manage the vast amount of information that they are exposed to in every class they attend daily. The simulation performed in this study established the greater importance of delving deeper and implementing a higher degree of diagnostic assessment based on the learners’ affective and cognitive domains as these directly affect the learners' academic performance. The combined values of a learner's attention, emotions, and cognition have significantly served as valuable inputs to determine which component has the most substantial influence on the learner's learning process. Correspondingly, the designed rule-based pedagogy in this study has provided essential insights that can be used as a guide in selecting the best-suited learning pedagogy for every student. The approaches implemented in this study also opened up new opportunities for AI integration into the current e-learning and academic environment. It can fundamentally help make the system more efficient and effective to assess the learners' progress and enhance the teaching-learning outcomes. To further improve this study, it is recommended to engage more experts to re-validate the prioritization of the proposed rule-based design and to employ an in-depth mathematical analysis to improve the usefulness of the aggregation functions.

References

Adesola, S.A., & Li, Y. (2018). Investigating the Impact of Learners Emotion Academic Performance and Motivation using Ethnography. International *Journal of Information and Education Technology, 8*(10). http://www.ijiet.org/vol8/1130-T12.pdf

Ahmad, M. I., Keller, I., Robb, D. A., & Lohan, K. S. (2020). A framework to estimate cognitive load using physiological data. *Personal and Ubiquitous Computing.* https://doi.org/10.1007/s00779-020-01455-7

Ahmad, K, Fugaha, A., Qadir, J., & Igbal, W. (2020). Artificial Intelligence in Education: A Panoramic Review. *EdArXiv Preprints.* https://doi.org/10.35542/osf.io/zvu2n

Ali, W. (2020). Online and Remote Learning in Higher Education Institutes: A Necessity in light of COVID-19 Pandemic. *Higher Education Studies, 10*(3). https://files.eric.ed.gov/fulltext/EJ1259642.pdf

Amadioha, S. W (2009). The Importance of Instructional Materials in our School: An Overview. *New Era Research Journal of Human, Educational and Sustainable Development*, 2, 4–9. https://www.researchgate.net/publication/322368912

Braude, S., & Dwarjka, V. (2020). Teachers' experiences of supporting learners with attention-deficit hyperactivity disorder: Lessons for professional development of teachers. *South African Journal of Childhood Education.* https://sajce.co.za/index.php/sajce/article/view/843/1650

Bradbury, N. A., (2016). Attention span during lectures: 8 seconds, 10 minutes, or more?. *Advances Physiology Education*, 40, 509–513. https://doi.org/10.1152/advan.00109.2016

Butt, M. N., & Iqbal, M. (2011). Teachers Perception Regarding Facial Expressions as An Effective Teaching Tool. *Contemporary Issues in Education Research (CIER), 4*(2), 11–14. https://doi.org/10.19030/cier.v4i2.4077

Chisari, L. B., Mockevičiūtė, A., Ruitenburg, S. K., Vemde, L., Kok, E. M., & Gog, T. (2020). Effects of prior knowledge and joint Attention on learning from eye movement modelling examples. *Journal of Computer Assisted Learning, 36*(4), 569–579. https://doi.org/10.1111/jcal.12428

Mu, S., Cui, M., Wang, X. J., Qiao, J. X., & Tang, D. M. (2019). Learners' attention preferences of information in online learning. *Interactive Technology and Smart Education, 16*(3), 186–203. https://doi.org/10.1108/ITSE-10-2018-0090

Costley, J., (2019). Using Cognitive Strategies Overcomes Cognitive Load in Online Learning Environments. *Interactive Technology and Smart Education, 17*(2), 215–228. https://doi.org/10.1108/ITSE-09-2019-0053

Costescu, C., Rosan, A., Brigitta, N., Hathazi, A., Kovari, A., Katona, J., Demeter, R., Heldal, I., Helgesen, C., Thill, S., & Efrem, I. (2019). Assessing Visual Attention in Children Using GP3 Eye Tracker. *10th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, 343–348. https://doi.org/10.1109/CogInfoCom47531.2019.9089995

Deng, J., & Ren, F. (2020). Multi-Label Emotion Detection via Emotion Specified Feature Extraction and Emotion Correlation Learning. *IEEE Transactions on Affective Computing*. https://ieeexplore.ieee.org/document/9241233

Dores, A.R, Barbosa, F, Queiros, C, Cavalho, I.R., & Griffith, M.D. (2020). Recognizing Emotions through Facial Expression: A Largescale Experimental Study. *International Journal of Environment Research and Public Health, 17*(20), 7420. https://doi.org/10.3390/ijerph17207420

Ellah, B.O., Anchor, E.E. & Enemarie, V. (2019). Problem-Solving Skills as Correlates of Attention Span and Working Memory of Low Ability Level Students in Senior Secondary Schools. *Journal of Education and e-Learning Research,* 6(3), 135–141. http://doi: 10.20448/journal.509.2019.63.135.141

El Kerdawy, M., El Halaby, M., Hassan, A., Maher, M., Fayed, H., Shawky, D., & Badawi, A. (2020). The Automatic Detection of Cognition Using EEG and Facial Expressions. *Sensors, 20*(12), 3516. https://doi.org/10.3390/s20123516

Farisha, A.T.P, Salam, R., Nourin, N., & Fathima, N. (2019). Gender Differences in Visual Scanning, Response Speed and Sustained Attention. *Journal of Psychosocial Research, 14*(1), 123–131. https://doi.org/10.32381/JPR.2019.14.01.1

Ghorbani,S., Dana, A & Fallah, Z., (2019). The Effects of External and Internal Focus of Attention on Motor Learning and Promoting Learner's Focus. *Biomedical Human Kinetics, 11*(1), 175–180. https://doi.org/10.2478/bhk-2019-0024

Hascher, T., (2010). Learning and Emotion: Perspective for Theory and Research. *European Educational Research Journal, 9*(1), 13–28. https://doi.org/10.2304/eerj.2010.9.1.13

Hettiarachchi, I., Hanoun, S., Nahavandi, D., Iskander, J., Hossny, M., & Nahavandi, S. (2018). *Towards More Accessible Physiological Data for Assessment of Cognitive Load—A Validation Study*. IEEE International Conference on Systems, Man, and Cybernetics (SMC), 3045–3050. https://doi.org/10.1109/SMC.2018.00517

Hewson, E.R., (2018). Students' Emotional Engagement, Motivation and Behaviour Over the Life of an Online Course: Reflections on Two Market Research Case Studies. *Journal of Interactive Media in Education*, 10, 1–13, https://doi.org/10.5334/jime.472

Hlas, A.N., Neyers, K., & Molitor, S. (2019). Measuring Student Attention in the Second Language Classroom. *Language Teaching Research, 23*(1), 107–125. https://doi.org/10.1177/1362168817713766

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education Promises and Implications for Teaching and Learning. Center for Curriculum Redesign*. https://curriculumredesign.org/wp-content/uploads/AIED-Book-Excerpt-CCR.pdf

Huang, Y.-M., Cheng, Y.-P., Cheng, S.-C., & Chen, Y.-Y. (2020). Exploring the Correlation Between Attention and Cognitive Load Through Association Rule Mining by Using a Brainwave Sensing Headband. *IEEE Access*, 8, 38880–38891.https://doi.org/10.1109/ACCESS.2020.2975054

Hwang, G.J., & Tu, Y.F. (2021). Roles and Research Trends of Artificial Intelligence in Mathematics Education: A Bibliometric Mapping Analysis and Systematic Review. *Mathematics, 9*(6), 584. https://doi.org/10.3390/math9060584

Jia, S., Wang, S, Hu, C., Webster. P.J., & Li, X. (2021). Detection of Genuine and Posed Facial Expressions of Emotion: Databases and Methods. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2020.580287

Joo-Hee, K., Euijin, K., Chang, I., & Do-Won, K. (2018). *Classification of Different Cognitive Load using Electroencephalogram (EEG): A Preliminary Study.* Joint 10th International Conference on Soft Computing and Intelligent Systems and 19th International Symposium on Advanced Intelligent System (ISIS), 205–208. https://doi.org/10.1109/SCIS- ISIS.2018.00043

Kalpanadevi, D. (2019). *Design and Implementation of Human-computer interface based Cognitive Model for Examine, the Skill Factor of Students.* 3rd International Conference on Computing Methodologies and Communication (ICCMC) ,737–742. https://doi.org/10.1109/ICCMC.2019.8819794

Kaur, N., Arora, J., Dwivedi, D., & Gandhi, A. (2020). Study of the Effectiveness of E-Learning to Conventional Teaching in Medical Undergraduates Amid COVID-19 Pandemic. *National Journal of Physiology, Pharmacy and Pharmacology, 10*(7), 563–567. https:// https://doi.org/10.5455/njppp.2020.10.04096202028042020

Li, D., Wang, Z., Wang, C., Liu, S., Chi, W., Dong, E., Song, X., Gao, Q., & Song, Y. (2019). The Fusion of Electroencephalography and Facial Expression for Continuous Emotion Recognition. *IEEE Access*, 7, 155724–155736. https://doi.org/10.1109/ACCESS.2019.2949707

Lindner, A. (2019). T*eacher's Perspective in Artificial Intelligence*. ISSEP 12th International Conference on Informatics in Schools, p. 22–29. https://cyprusconferences.org/issep2019/wp-content/uploads/2019/10/LocalISSEP-v5.pdf

Liu, Y., Lim, W. L., Hou, X., Sourina, O., & Wang, L. (2015). Prediction of Human Cognitive Abilities Based on EEG Measurements. *International Conference on Cyberworlds (CW),* 161–164. https://doi.org/10.1109/CW.2015.47

Lodge, J.M., Kennedy, G., Lockyer, L., Arguel, L.L., & Pachman, M. (2018). Understanding Difficulties and Resulting Confusion in Learning: Integrative Review. *Frontiers in Education.* https://doi.org/10.3389/feduc.2018.00049

Moroto, Y., Maeda, K., Ogawa , T., & Haseyama, M., (2020). Human- Centric Emotion Estimation Based on Correlation Maximization Considering Changes with Time in Visual Attention and Brain, Activity. *IEEE Access,* 8, 203358–203368. https://doi.org/10.1109/ACCESS.2020.3036908

Mukhopadhyay, M, Pal, S., Nayyar, A., Pramanik, P.K.D., Dasgupta, N., & Chouhurry, P. (2020). Facial Emotion Detection to Assess Learner's Mind in an Online Learning System. *International Conference on Intelligent Information Technology*. https://doi.org/10.1145/3385209.3385231

Paas, F & Merrienboer, J.J.G.V, (2020). Cognitive -Load Theory: Methods to Manage Working Memory Load in the Learning of Complex Tasks. *Current Directions in Psychological Science,* 29(4), 392–398. https://doi.org/10.1177/0963721420922183

Peng, P., & Kievit, R.A. (2020). The Development of Academic Achievement and Cognitive Abilities: A Bidirectional Perspective. *Child Development Perspectives, 14*(1),15–20. https://doi.org/10.1111/cdep.12352

Permana, I., Firman, H., Redjek, I., & Hamidah, I. (2019). Applying of Teaching Strategy based on Cognitive Load Theory to Develop Pre- Service Teacher Teaching Skills of Waves: Cognitive Load Analysis. International Conference on Mathematics and Science Education. *Journal of Physics: Conference Series, 1157*(2):022026. https://doi.org/ 10.1088/1742-6596/1157/2/022026

Qin, Y., Zhang, Y., & Jia, Y. (2020). *The Research about the Role and Influence of Teacher Emotional Support in Online Environment.* https://www.researchgate.net/publication/343178746_The_Research_about_the_Role_and_influence_of_Teacher_emotional_support_in_Online_Learning_Environment

Ratniece, D., (2018). Cognitive Development in Active eLearning. *International Journal of Engineering & Technology, 7*(2):53-57. https://doi.org/10.14419/ijet.v7i2.28.12881

Revadekar, A., Oak, S., Gadekar, A., & Bide, P. (2020). Gauging attention of students in an e-learning environment. *IEEE 4th Conference on Information & Communication Technology (CICT),* 1–6. https://doi.org/10.1109/CICT51604.2020.9312048

Songkram,N., Khlaisang, J., Puthaseranee, B., & Likhitdamrongkiat, M., (2014). E-learning system to enhance cognitive skills for learners in higher Education. *Social and Behavioral Sciences, 174*(2015), 667–673. https://doi.org/10.1016/j.sbspro.2015.01.599

Shao K., Pekrun, R., & Nicholson, L.J (2019). Emotions in Classroom Language Learning from Achievement Emotion Research?. *Elsevier*, 86. https://doi.org/10.1016/j.system.2019.102121

Sun, A., & Chen, X. (2016). Online Education and its Effective Practice: A Research Review. *Journal of Information Technology Education: Research*, 15, 157-190. https://doi.org/28945/3502

Tremolada, M., Taverna, L., & Bonichini, S. (2018). Which Factors Influence Attentional Functions? Attention Assessed by KiTAP in 105 6-to-10-Year-Old Children. *Behavioral Sciences, 9*(1), 7. https://doi.org/10.3390/bs9010007

Tachie, S. A. (2019). Meta-cognitive Skills and Strategies Application: How this Helps Learners in Mathematics Problem-solving. *EURASIA Journal of Mathematics, Science and Technology Education, 15*(5). https://doi.org/10.29333/ejmste/105364

Tremolada, M., Taverna, L., & Bonichini, S., (2018). Which Factors Influence Attentional Functions? Attention Assessed by KiTAP in 105 6- to-10-Year-Old Children. *Behavioral Sciences, 9*(1), 7. https://doi.org/10.3390/bs9010007

Valverde-Berrocoso, J., Garrido-Arroyo, M. del C., Burgos-Videla, C., & Morales-Cevallos, M. B. (2020). Trends in Educational Research about e- Learning: A Systematic Literature Review. *Sustainability, 12*(12), 5153. https://doi.org/10.3390/su12125153

Williams, N.S., McArthur, G., & Badcock, NA (2020). 10 years of EPOC: A Scoping review of Emotiv's portable EEG device. *bioRxiv: The Preprint for Biology*. https://doi.org/10.1101/2020.07.14.202085

Winn, A.S, DelSignore, L., Marcus, C., Chiel, L., Freiman, E., Stanford., D & Newman, L. (2019). Applying Cognitive Learning Strategies to Enhance Learning and Retention in Clinical Teaching Settings. *The AAMC Journal of Teaching and Learning Resources.* https://doi.org/10.15766/mep_2374-8265.10850

Yuan, X., & Yang, C. (2019). Attention-Based User Temporal Model for Recommendation. I*EEE 5th International Conference on Computer and Communications (ICCC)*, 1877–1880. https://doi.org/10.1109/ICCC47050.2019.9064186

Zawacki-Richter, O., Marin, V.I, Bond, M., & Gouverneur, F. (2019). Systematic Review of Research on Artificial Intelligence Applications in Higher Education- Where are the Educators?. *International Journal of Educational Technology in Higher Education.* https://doi.org/10.1186/s41239-019-0171-0

Zhang, J., Mo, Y., Chen, C., & He, X. (2020). Neural Attentive Knowledge Tracing Model for Student Performance Prediction. *IEEE International Conference on Knowledge Graph (ICKG)*, 641–648. https://doi.org/10.1109/ICBK50248.2020.00096