Education and Information Technologies (2022) 27:9913–9934
https://doi.org/10.1007/s10639-022-11010-x

A machine learning enabled affective E-learning system model

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Received: 22 December 2021 / Accepted: 16 March 2022 / Published online: 6 April 2022

Abstract
The purpose of this study is to propose an e-learning system model for learning content personalisation based on students' emotions. The proposed system collects learners' brainwaves using a portable Electroencephalogram and processes them via a supervised machine learning algorithm, named K-nearest neighbours (KNN), to recognise real-time emotional status. Besides, it uses a reinforcement learning approach to analyse the learners' emotional states and automatically recommend the best-fitted content that keeps the students in a positive mood. The performance of the proposed system is evaluated in two forms: 1) the system performance and 2) student engagement, satisfaction, and learning. A convenience sampling method is used to select 30 students from the pollution of 281 PartII-undergraduate students who study computer science during the 2020-21 academic year at the University of Nottingham Ningbo China. The selected students are divided into homogenous control and experimental groups for learning English listening and reading skills. According to the machine learning results, the trained KNN recognises the emotional states with an accuracy of 74.3%, the precision of 70.8%, and recall of 69.3%. In addition, the results of the t-Test demonstrate that the proposed e-learning system model has no significant impact on learners' learning and engagement but enhances the student's satisfaction compared to traditional e-learning systems ($p < 0.05$).

Keywords Affective learning · EEG · Machine learning · E-learning

Xinyang Liu and Saeid Pourroostaei Ardakani contributed equally to this work.

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1 Introduction

Online educational systems (i.e., e-learning) are increasingly becoming popular due to the risks of face-to-face lectures during the COVID-19 pandemic (Velavan & Meyer, 2020). However, they usually avoid real-time students' feedback analysis and fail to deliver appropriate teaching content. Teachers usually observe the learners and analyse their feedback to personalise the teaching materials and meet the student's requirements. But, they usually experience several challenges due to the lack of a standard analysis approach, feedback system and observation method. Affective learning is a potential solution to resolve this drawback and improve the quality of Teaching and Learning (T&L) (King & Chen, 2019). It has the potential to enhance students' satisfaction, engagement, and learning, especially where face-to-face teacher-student interaction is restricted (e.g., e-learning) (Ahmadi & Reza, 2018).

Affective T&L systems provide the students with personalised content according to their emotional status, feeling, or mood (Saito et al., 2018). For example, they may deliver edutainments (e.g., educational games) instead of textbooks if the learners feel bored or sad, while it provides the students with additional teaching content if they feel happy (Madani et al., 2019). For this, the system collects learners' emotional cues (e.g., brainwaves) and analyses the data to provide the students with the best-fitted teaching materials according to their skills, requirements, characteristics and capacities (Shao et al., 2019). In other words, they aim to keep the learners connected and engaged and enhance their attention and satisfaction during lectures (Malone et al., 2019). They have the capacity to offer T&L several benefits -mainly support diversity and inclusion.

Machine Learning (ML) techniques can be used to explore T&L data patterns and personalise educational content. They have the capacity to explore emotional data patterns (e.g., facial expressions or brainwaves) and classify the best-fitted/personalised teaching content according to students' emotional status. Moreover, it delivers the teaching content manually (i.e., teacher intervention) or automatically (i.e., machine decision making) (Chen et al., 2020). The former allows the teacher for choosing the teaching content by analysing the reported students' affect, while the latter trains ML models to learn the correlation between learning materials and learners' emotions and automatically deliver the best-fitted ones (Kandel et al., 2013). However, there are still a few questions in this field of research that should be taken into account:

1. Which data features should be used for an ML model training to address T&L application requirements (e.g., personalisation)?
2. How the ML model should be designed and trained to meet the data analysis objectives (i.e., real-time emotion classification) with an optimised performance (e.g., accuracy)?
3. How to evaluate the performance of ML applications to measure their functionality and robustness?

Electroencephalogram (EEG) is widely used to capture high-quality brainwaves (i.e., 1 to 80Hz) and recognise emotional states. Indeed, EEG data is analysed to extract affective/arousal features and recognise emotional status (Suhaimi et al., 2020). It measures neuron activity (i.e., voltages) in the brain cortex using specific electrodes and classifies them based on frequency bands such as alpha (8-12Hz) and beta (12-30Hz). Each of the EEG's frequency bands should be interpreted to highlight a particular mental activity/state. For example, the alpha band is usually used to detect brain inactivity, whereas beta shows the active mental states.

This paper proposes an affective educational system model that aims to personalise teaching contents according to the learner's emotional status. It takes the benefit of machine learning techniques (i.e., KNN) to analyse learners' EEG signals and recognise their emotional states. Moreover, the proposed system uses a reinforcement learning approach to personalise teaching content based on the learner's emotional state. Figure 1 depicts the system's sequence diagram and highlights the interactions between the system components. This research deploys the proposed educational system for English skills including reading and listening. It tests the performance and functionality of the proposed system in terms of students' learning, engagement, and satisfaction according to an experimental plan with control and experimental student groups. The key contributions of this research are outlined as below:

1. To propose a KNN ML model to classify EEG signals and recognise emotional states.
2. To propose reinforcement learning approach to personalise teaching according to the learners' emotion.
3. To deploy and test an affective e-learning system for English skills (i.e., reading and listening).
4. To evaluate the performance of the proposed system in terms of learner's learning, engagement, and satisfaction.

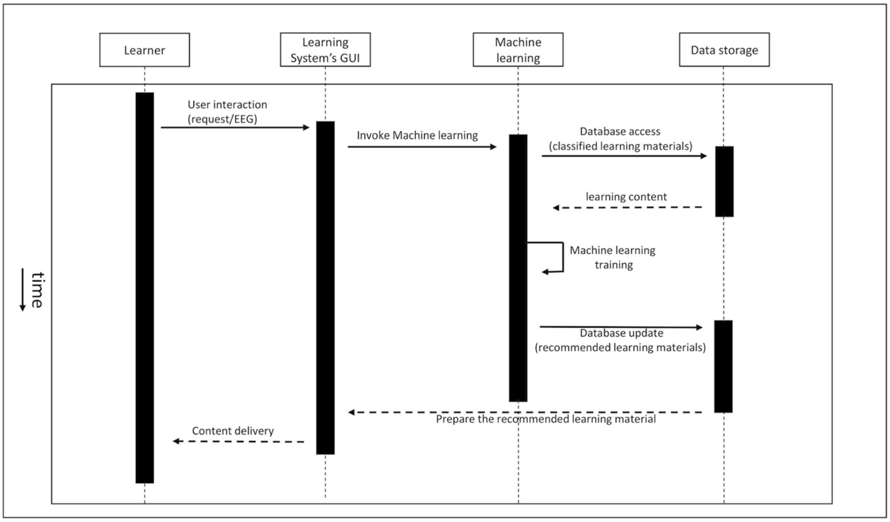

Fig. 1 The proposed system's sequential diagram

The rest of this paper is organised as follows. Section 2 reviews literature in the field of affective learning, emotion recognition, and machine learning, particularly for e-learning. Section 3 describes the research methodology and presents the evaluation plan. Section 4 discusses the results and outlines key findings. Section 5 concludes this research and highlights the issues that should be addressed as further work.

2 Related works

Emotion is a psychological concept, which is classified into two main categories (Costanzi et al., 2019): primary and complex. The former is comprised of six emotional states including happiness, sadness, surprise, anger, disgust, and fear, while the latter (e.g., pride and afraid) is formed as the combination of some primary emotions.

2.1 Russell's circumplex model

Russell's circumplex model (Posner et al., 2005) conceptualise emotional states as the result of a linear combination of two independent parameters: arousal and valance. For example, angry emotion addresses strong positive arousal and negative valance. Arousal is the physiological output of the Autonomic Nervous System (ANS) (Citron et al., 2014). It focuses on the intensity and strength of emotional statuses and is measured through physiological cues such as heart rate, blood pressure, and/or brain signals (Herman et al., 2018). Emotional valance refers to the attractiveness and pleasantness of events resulting in positive or negative feelings (Berridge, 2019). It can be measured through self-report questionaries, facial expression observations and/or brain signal analysis (Hidalgo-Munoz et al., 2017). Figure 2 shows, the Russell's circumplex model (Posner et al., 2005).

Russell's circumplex model is used by EEG signals processing approaches to recognise emotional features (Galvão et al., 2021). EEG signals are analysed using signal processing approaches (i.e., Mel-Frequency Cepstral Coefficients and Kernel Density Estimation (Othman et al., 2013)) to extract meaningful brainwave features and label the EEG electrodes according to the arousal and valance (Apicella et al., 2021) and (Aydin et al., 2016). According to (Coan et al., 2001), the greater left frontal brain is in charge of positive emotions, while the right frontal brain electrodes report negative emotions. Machine learning techniques (i.e., Convolutional Neural Network (Garg & Verma, 2020)) classify the valance-arousal features and recognise the emotional state (Bazgir et al., 2018).

2.2 Emotional status recognition

Emotion recognition techniques (Narayanan, 2012) aim to interpret affective cues such as facial expression, voice, gesture and physiological signals. They can be categorised into two classes: non-physiological and physiological. Facial expression is the most commonly used non-physiological approach that conveys affective signs, especially during

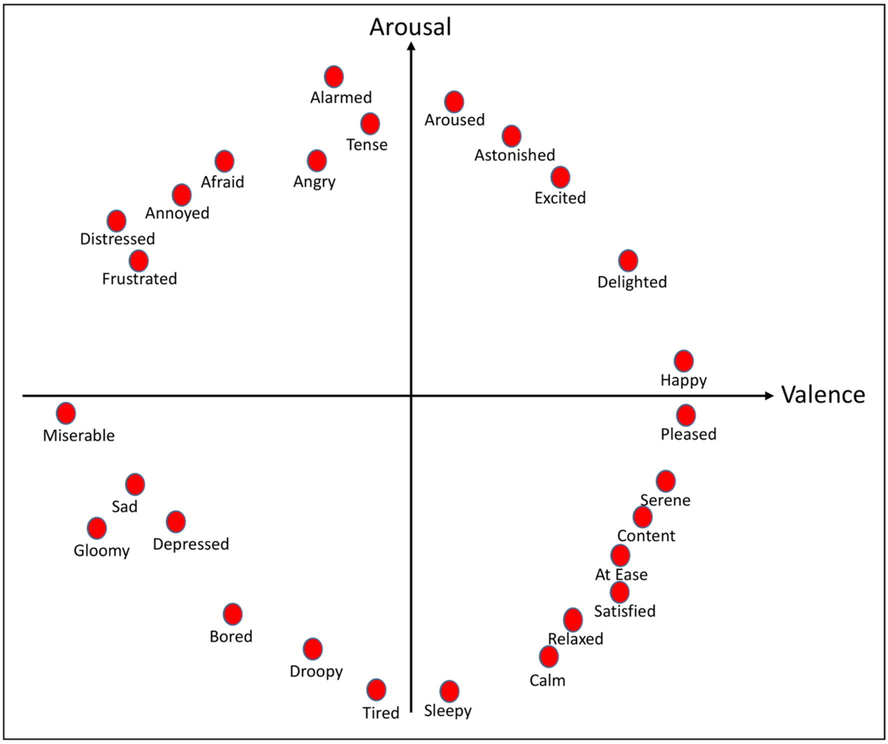

Fig. 2 Russells-circumplex-model

face-to-face communications. According to Yang et al. (2018), face muscle movements address affective facial expression based on the individual's emotional states. It can be recognised using computing techniques -mainly image processing. Teachers usually use facial expressions during face-to-face teaching to monitor students' engagement and satisfaction. However, facial expressions may be influenced by external factors such as culture, age and hairstyle that results in wrong emotional state interpretation. This drawback can be resolved if physiological cues such as heartbeat, blood pressure, and brain signals are analysed to recognise emotional states (Li et al., 2018). Hu et al. (2016) reports that the Correlation-based Feature Selection KNN machine learning technique analyses EEG data to recognise emotional status with an accuracy of 80.84%. However, physiological cue collection and interpretation is expensive and complicated as it needs specifics equipment (e.g., sensors) and data analysis method (e.g., signal processing).

Shen et al. (2009) develop an affective e-learning platform that collects and interprets learners' physiological cues such as heart rate, skin conductivity, and blood pressure. It uses the Support Vector Machine (SVM) technique to classify physiological signals and recognise emotional states. This platform provides students with materials according to their emotional status. According to the results, an emotional state classification accuracy of 68.1% is achieved when physiological cues are used, whereas it is increased to 86.3% when brain signals are analysed. It supports that brain signals work better to recognise emotional states.

2.3 Affective learning

Affective learning plays a key role in education to improve students' engagement, satisfaction and learning (Tyng et al., 2017; Schmidt, 2017; McConnell and Eva, 2012). In other words, students are actively engaged with teaching materials and learn better if they feel positive during a lecture. It is because of the impact of emotion on attention, memory, and mental agility during T&L sessions.

Heron (Malone et al., 2019) proposes a multimodal learning model to study the relationship between emotion and cognition. This study aims to link learners' emotions and cognition factors (i.e., attention, memory, and decision-making) during a teaching session. It results in increased learning achievements and improved learners' satisfaction. O'regan (2003) investigates the impact of emotion on online learning. For this, 11 students use questionnaires to report their emotional and learning experiences after participating in an e-learning programme. According to the results, it is concluded that better learning is achieved when students have positive emotions.

Affective learning can be used for various e-learning applications -mainly foreign language learning (Shao et al., 2019). Zhu and Zhou (2012) reports that affective learning has the capacity to eliminate the impact of negative emotions (e.g., anxiety and depression) on foreign language learning for middle school students who often feel bored in the lectures and have foreign language learning difficulties. Kazuya Saito (Saito et al., 2018) extends this research to investigate the impact of emotion on learning foreign languages for 108 high school students who study English as a second language. The results show that students are actively engaged in the lectures and learn better if they feel positive (i.e., happy) during the English lecture.

2.4 Machine learning in e-learning system

Machine learning techniques are increasingly used in e-learning applications to process and analyse T&L data patterns. They have the capacity to support course/material recommendation functions by analysing the students' feedback and behaviour in real-time. This means, ML techniques automatically classify and personalise the learning materials according to learners' preferences and/or feeling (Jang et al., 2019). For example, Aher and Lobo (2013) utilises a combination of k-means clustering and association rule technique to recommend students relevant courses according to their preferences.

Reinforcement learning (RL) is a model-free ML technique that learns through an environment exploration-exploitation paradigm (Sutton & Barto, 2018). It has the capacity to offer e-learning systems benefits by providing the learners with the best-fitted and/or personalised learning materials according to their preferences or conditions (Ammar et al., 2010). However, determining a learning strategy is still seen as a Markov model (Even-Dar et al., 2004), in which the learner state (e.g., preference, and/or affective states) depends on the existing learning records and the delivered materials.

RL explores the learning environment (i.e., learning preferences) to update an award function (i.e., best-fitted materials) which is calculated according to the taken actions (i.e., teaching material selection). It has the capacity to enhance the performance of the learning system when learners receive best-fitted materials with minimised latency (i.e., in real-time) and maximised quality/relevance. Madani (2019) proposes an e-learning system that uses RL to recommend teaching content. It analyses learners' characteristics (e.g., background knowledge) to find the best-fitted learning materials. For example, fast learners are forwarded to the next teaching topics, whereas slow learners may receive further examples to understand the learning topics.

This literature review supports the role of affective learning in e-learning environments and outlines the existing applications that take the benefit of ML techniques to improve T&L (e.g., students' learning, engagement and satisfaction). Moreover, it uncovers that EEG data analysis is a promising and accurate approach to classify/predict emotional states in e-learning applications. However, there is still a lack of research to propose an ML-enabled course/material personalisation function in affective e-learning environments. It should be able to analyse EEG data, classify emotional states, and automagically provide learners with the best-fitted teaching materials according to their emotional status.

3 Methodology

This research proposes an educational system model that has the capacity to personalise teaching content according to students' emotional status. Indeed, it aims to keep or make the students motivated during a lecture. The proposed system provides students with educational entertainment (i.e., funny videos) if they feel negative (e.g., bored), while it delivers further learning materials (i.e., classified text/audio) if the learners are in positive emotional states (e.g., happy). As Fig. 3 shows, the proposed system collects students brainwaves in real-time and analyse them using a machine learning classification technique (i.e., KNN) to recognise their emotional status. In turn, a reinforcement learning approach is used to learn the best-fitted teaching materials that keep the students positive during a teaching session. By this, the research methodology consists of three keys as below:

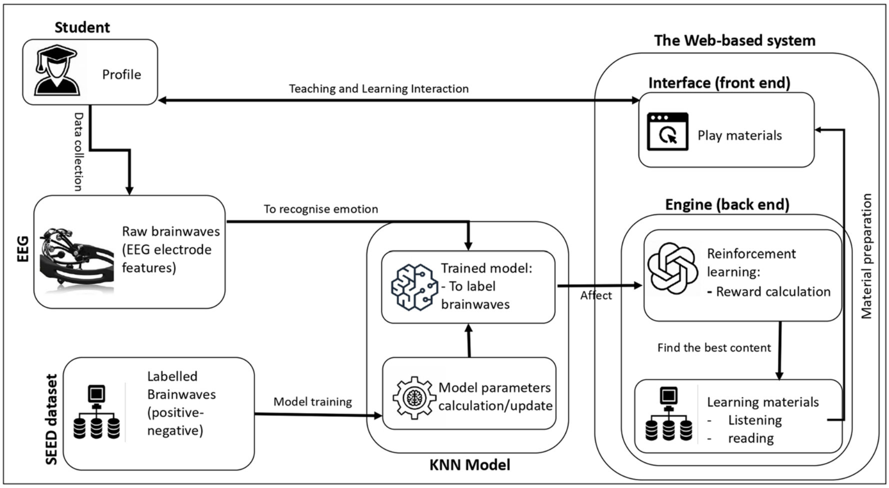

Fig. 3 The operational framework diagram

1. Train an ML classification model to recognise user emotional status (i.e., KNN)
2. Propose a reinforcement learning approach (i.e., Q-learning) to enable teaching content personalisation according to the students' emotional statuses.
3. Design an experimental plan to test the performance of the proposed e-learning system in terms of students' learning, engagement, and stratification.

The proposed system collects EEG signals and classifies them using a KNN classification model as Algorithm 1 to recognise users' emotional states. It uses wearable EEG equipment, named EMOTIV EPOC+ (Emotiv, 2021), to record users' brainwaves. EMOTIV EPOC+ is a portable, small-size and low-cost wireless EEG headset that consists of 14 data-collection and 2 reference electrodes.

Algorithm 1 KNN Algorithm.

```
Require:
/*n training samples (emotion labels)*/
A[n];
/*the nearest neighbour number (label value)*/
k;
/*new sample*/
x;

Ensure:
/*the class/label of x*/
k_labels;
/*initial KNN of x*/
A[1]~ A[k];
/*Calculate Euclidean distance between test and x samples*/
Ed(x, A[i]): i = 1, 2..., k;
/*Sort ascending order*/
Sort (Ed (x, A[i]));
/*Calculate the distance D between the furthest sample and x*/
D = Max (Ed (x, A[i]));

/*Calculate the Euclidean distance between A[i] and x*/
for (i = k + 1; i <= n; i + +){
        Ed (x, A[i]);
        If (Ed(x, A[i]) < D){
                Replace the farthest sample with A[i];
                /*Sort Ed(x,A[i]), ascending order*/
                 sort (Ed (x, A[i]));
                /*Calculate D between the furthest sample and x*/
                 D = Max (Ed (x, A[i]));
                 }/*End of If*/
        } /*End of For*/

/*Calculate the probability of first k samples in category*/
k_labels = label (A[Top_k_index]);
/*The class with greatest probability is the class of sample x*/
Result = Max_prob(k_labels);
```

This research utilizes the KNN classification technique because it is simple to implement and suitable for non-linear relationships between the classfication inputs and outputs. The KNN model is trained using the SJTU Emotion EEG Dataset (SEED) (Zheng & Lu, 2015) to classify EEG's data into three emotional classes of positive valance (e.g., relaxed, and happy), neutral (i.e., neutral), and negative valance (e.g., sad and bored). SEED is a well-known, reliable, and high-quality EEG dataset that is collected and verified by Shanghai Jiao Tong University in 2015. SEED supports EMOTIV EPOC+ feature labelling and contains annotated EEG data (i.e., positive, neutral, and negative valence) that is collected from 15 groups of subjects (7 males and 8 females; MEAN: 23.27, STD: 2.37) during 15 affective clips each of which lasts for 4 minutes (Lan et al., 2018). The original SEED was divided into 75% train and 25% test parts. The former was used to train the model, while the latter was used to evaluate the model. According to the results, the KNN model is able to recognise the emotional statues with an accuracy of 74.3%, a precision of 70.8%, and a recall of 69.3%. Accuracy, precision and recall are introduced as below:

1. *Accuracy:* is the percentage of True predictions based on the total number of predictions. It is the most commonly used measure to evaluate the performance of an ML model. It is calculated using Eq. 1, where TP is the number of True Positive predictions, FP shows False Positive predictions, TN refers to True Negative predictions, and FN is False Negative predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

2. *Precision:* is used to show the model capacity to predict a positive emotional state. It isa used to interpret the number of positive emotion cases which are classified as negative. It is calculated via the following equation:

$$\frac{TP}{TP + FP} \tag{2}$$

3. *Recall:* or Sensitivity measures the percentage of total positive predicted emotional states to the number of actual positive emotional states in the dataset. Hence, a model is more sensitive if it has a higher recall is achieved. The recall is calculated as below:

$$\frac{TP}{TP + FN} \tag{3}$$

The proposed e-learning system model uses a reinforcement learning technique for personalising the learning materials. Indeed, it provides the learners with the best-fitted learning materials according to their emotional status. The objective is to keep the students in positive valance emotions (i.e., happy and relaxed) during a teaching session. As Fig. 4 shows, the reinforcement learning algorithm collects and analyses the learner's feedback data (i.e., EEG collected brainwaves) according to the system's actions (i.e., recommended materials). In other words, RL's states are formed as the learner's affective state, whereas the algorithm's actions are defined by the recommended materials (i.e., text or entertainment). Yet, the proposed reinforcement learning algorithm calculates a reward value according to the states (i.e., emotional status) that are updated by the actions (i.e., recommended learning materials). The maximum reward value shows the best-fitted action that is able to keep the students in positive mode longer.

This research uses Q-learning technique (Van Hasselt et al., 2015) to build the personalisation system. Q-learning's agent takes actions (A) to learn and update the states (S). For this, each action is assigned by an initial value (i.e., A_t) and generates a reward for the entire model once the state changes (S->Q). As Eq. 4 shows, α is the learning rate, R is the action reward, and γ is the discount factor. The α ($\in$ (0, 1)) shows how the algorithm is able to quickly learn, while γ ($\in$ (0, 1)) is used to control the number of rewards. According to (Even-Dar & Mansour, 2003), the proposed Q-learning algorithm is tuned with α value of 0.01 and γ value of 0.9 in this research.

$$\begin{aligned} Q(S_t, A_t) \leftarrow\ & Q(S_t, A_t) \\ & + \alpha\left[R_t + \gamma \times max_A Q(S_{t+1}, A) - Q(S_t, A_t)\right] \end{aligned} \tag{4}$$

3.1 Experimental plan

This section describes an experimental research plan to test and evaluate the impact of the proposed system on students' learning, engagement and satisfaction. Learning is defined as the acquisition of new knowledge, attitude, behaviour and/or skill according to a pedagogical programme. Student engagement is the level of student's attention, effort and activity during learning, whereas satisfaction focuses on short-term student's feedback. Student engagement and satisfaction play a key role in increasing the learning (Trowler & Trowler, 2010) and (Korobova & Starobin, 2015).

The study population was PartII undergraduate students (age of 21-24 years) who study computer science during the 2020-21 academic year at the University of Nottingham Ningbo China (281 students). This research used a convenience sampling method to select 30 non-English speaking students with an academic International English Language Testing System (IELTS) certificate (total:6.00, reading: 6.50, listening: 6.50 listening). By this, 24 male and 6 female Chinese students (Age-mean: 22.13, Age-Standard Deviation: 1.84) were selected as the participants. The male and female participants were independently and randomly divided into two groups of 15, each of which with 12 males and 3 females. By this, two consistent and homogenous groups were formed as control and experimental. The control group was given a standard web-based English lecture as reading and listening, while the experimental group used the proposed system to receive the learning materials according to their affective status. The EMOTIV EPOC+ EEG was used to collect brainwaves from the experimental group while learning. The collected brainwaves were classified using the trained KNN model to recognize real-time emotional states. All the experiments were conducted in a quiet room with a temperature of 23 degrees Celsius and constant noise and air humidity to minimise the impact of external and environmental factors (e.g., noise, temperature and humidity).

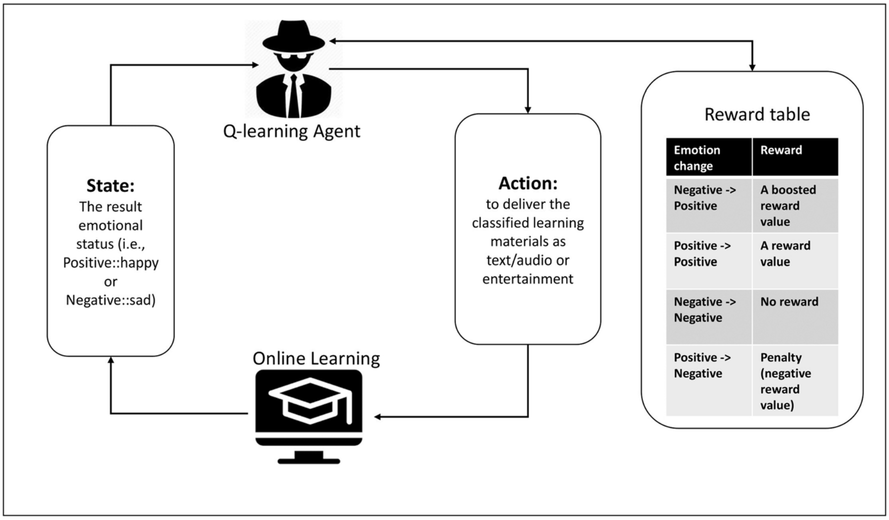

Fig. 4 Learning material recommendation using reinforcement learning

This research uses one multiple-choice test and two well-known and validated questionnaires to evaluate the performance of the proposed system in terms of students' learning, engagement, and satisfaction. The students' learning is measured according to two English language skills: reading and listening. For this, the students need to complete 20 multi-choice IELTS reading and listening tests according to a pre/post-test paradigm. A questionnaire (Commissiong, 2020) (Appendix A) is used to measure student engagement. It is comprised of 13 questions focusing on four aspects including skill and effort, connection with the learning materials, system interaction, and learning target achievement. Aman's questionnaire (Aman, 2009) (Appendix B) is used to evaluate the proposed system in terms of students' satisfaction. This questionnaire is comprised of 30 questions focusing on the learner's satisfaction with the educational system's interaction features that play a key role in students' satisfaction (Diekelmann & Mendias, 2005).

This article uses the Statistical Power Analysis (SPA) technique (Serqeant, 2021) to test the confidence of the sample size. SPA uses the standard deviation of a subset of the population (e.g., five samples) to calculate the number of observations based on an acceptable confidence level. According to the results, the sample size of 15 is sufficient to achieve a confidence level of 90% for data analysis in this research.

4 Results and discussion

This section presents and discusses the experimental results to address the research hypotheses as below:

1. H1: The proposed affective e-learning model will significantly impact student English learning in terms of reading and listening skills.

2. H2: The proposed affective e-learning model will positively affect student engagement during the online lecture.
3. H3: The proposed affective e-learning model will positively affect student satisfaction during the online lecture.

4.1 Results

This section utilises T-test to analyse the results due to the following reasons:

1. The sample size is small.
2. Data distribution is normal. According to Shapiro-Wilk (1965) results, the significance level of both reading and listening grades are 0.981 and 0.5966 respectively, while learners' engagement and satisfaction are 0.247 and 0.828. By this, the dataset meets a normal distribution as the significance levels are greater than 0.05 for all the features.

4.1.1 Learning

The learning results for both the control and experimental groups are collected from the test results. They are calibrated in a range of 0-1. Figure 5 shows and compares the reading and listening learning scores for both experimental and control groups. Moreover, Table 1 summarises the mean and standard deviation scores of the pre/post-listening and reading learning test for both groups.

An independent sample t-test is conducted on reading and listening scores of both pre or post-test groups to determine the learning difference between the groups. As Table 2 shows, both control and experiment groups report P-values that are greater than 0.05. Hence, the affective learning system has no significant impact on learning English learning in terms of reading and listening skills and hypothesis H1 is rejected.

According to the results, students' learning is not influenced by the affective educational system.

4.1.2 Learner's engagement

The impact of the affective learning system on learning engagement is studied by analysing the results of the engagement questionnaire. Table 3 shows, the mean and standard deviation of the learner's engagement questionnaire results.

Table 4 shows the t-test results for learner's engagement. According to it, there is no significant difference in student's engagement between the two groups as P-value is greater than 0.05. It rejects hypothesis H2.

4.1.3 Learner's satisfaction

The satisfaction questionnaire results are collected to analyse the impact of the affective learning system on students' satisfaction. Table 5 summarises the mean and standard deviation results of the learner's satisfaction questionnaire for both the control and experiment groups.

As Table 6 shows, the satisfaction questionnaire reports a p-value less than 0.05 that supports a significant difference in learner's satisfaction between the two groups. It accepts hypothesis H3.

4.2 Discussion

According to the results, the proposed system is able to impact satisfaction, while it fails to improve the students learning and engagement. It shows that teaching content personalisation based on learners' emotional status is not necessarily able to engage them with the teaching materials and improve learning. Student engagement and learning highly depend on student-teacher interaction, utilising critical thinking skills/activities, experiencing real-life examples, and/or group discussions. The proposed system is unable to enhance student engagement and learning because it offers no student-teacher interactions or learning activity enhancement benefits.

The results show that the proposed system impacts student satisfaction. Student satisfaction is highly correlated with the learning system features -mainly technology, accessibility, interactivity, simplicity and student support. Our approach is able to enhance satisfaction because it improves the system features. It is an intelligent T&L platform through which the students automatically are given the teaching content. They receive educational entertainment (i.e., videos) if they feel negative (e.g., bored), while

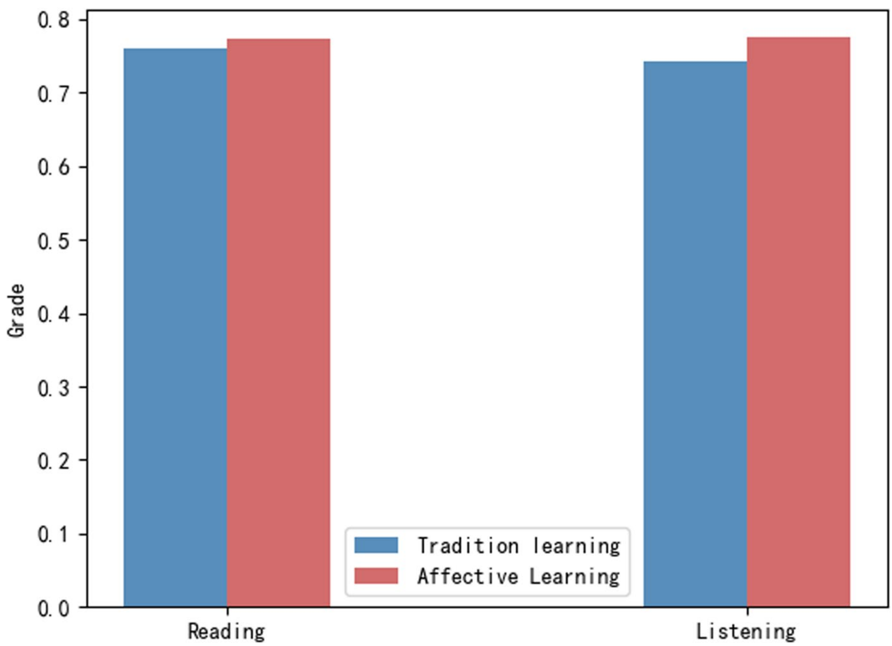

Fig. 5 Listening and reading normalised scores

Table 1 Total learning results

Group	Test	N	Mean	STD
Control	Pre-test	15	0.760	0.1121
Control	Post-test	15	0.773	0.1163
Experimental	Pre-test	15	0.741	0.0998
Experimental	Post-test	15	0.775	0.0615

Table 2 T-test results: Learning

Learning	T-value	DOF	P-value
Control	− 0.320	28	0.752
Experiment	− 1.100	28	0.281

Table 3 The results of engagement questionnaire

	N	Mean	Std.deviation
Control	15	4.1167	0.05382
Experiment	15	4.1667	0.07585

Table 4 T-test results: Engagement

	T-value	DOF	P-value
Engagement	− 0.538	28	0.595

they get further learning materials (i.e., classified text/audio) if they are in positive emotional states (e.g., happy). It provides the students with a supportive learning environment and improves their satisfaction.

5 Conclusion and further work

This research proposes an affective educational system model through which the learning materials are personalised according to their emotional states. This system classifies the learning materials according to two categories: entertainment (i.e., educational videos) and text/audio. By this, students who feel negative (e.g., bored) receive entrainments, while positive valance students are given further text/audio materials. A pre-trained KNN machine learning model (with an accuracy of 74.3%, a precision of 70.8%, and a recall of 69.3%) is used to classify students' brainwaves and recognise their emotional status. Moreover, a reinforcement learning approach is used to find the best-fitted learning materials according to the students emotional status.

The performance and functionality of the proposed system are tested and evaluated according to three key metrics including students' learning, engagement and satisfaction. An experimental group of students with 15 participants uses the

Table 5 The results of satisfaction questionnaire

Test	N	Mean	Std.deviation
Control	15	3.1500	0.03273
Experiment	15	3.8000	0.10965

affective system, while the control group (15 participants) utilises a traditional web-based online system for learning English reading and listening skills. The learning results are collected using a pre/post-English test, while the engagement and satisfaction are measured using two well-known questionnaires. According to the results, the proposed system has no impact on students' learning and engagement, whereas it has the capacity to enhance students' satisfaction.

The functionality of the proposed system model can be extended further where the impact of the system on further participants and other learning content (e.g., mathematics) is investigated. The performance of the Q-learning can be enhanced and the algorithm becomes robust if additional samples update the Q-table. In addition, it is still required to test the Q-learning where cognitive or constructive materials such as mathematics or geography are delivered.

The performance of the proposed system should be extended if further physiological data samples such as heart rate, skin conductivity and blood pressure are used to recognise the emotional states. Brainwave interpretation is complex as it can be influenced by a number of external factors (e.g., memories) during a learning session. It may return wrong emotion recognition results that significantly impact the performance of the proposed approach. However, the accuracy of emotion classification can be enhanced if additional features such as heart rate and skin conductivity samples are used for emotional state recognition.

As KNN is a lazy classification technique, it is still required to use other well-known supervised classification techniques such as Artificial Neural Network (ANN) and Support vector machines (SVM). By this, the proposed system will be able to recognise the students' emotional status with higher accuracy and personalise the teaching content efficiently.

Appendix A: Commissiong's student engagement questionnaire

Question		Answer
1.	Apply critical thinking skills to the course activities	·'Strongly Agree' (5) ·Agree (4)

Table 6 T-test results: Satisfaction

	T-value	DOF	P-value
Satisfaction	– 5.680	28	0.000

Question		Answer
		·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
2.	Integrate my won views with that of others when learning the course material	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
3.	Prepare study notes to understand the course material	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
4.	Apply my learning of the course material to real-time situations	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
5.	Interact with instructors at least once a week about the course material	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
6.	Discuss academic performance and other matters related to the achievement of academic goals with my instructors	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
7.	Obtain meaning feedback on assignments from instructors	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
8.	Understand difficult concepts and content better after interacting with instructors	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
9.	Collaborate with my peers in a one-to-one group relationship	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)

Question		Answer
10.	Interact with peers on mastering the course materials at-least once a week	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
11.	Respect peer differences	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
12.	Value peer differences	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)
13.	Use the online learning space to the course activities	·'Strongly Agree' (5) ·Agree (4) ·Neither Agree nor Disagree (3) ·Disagree (2) ·Strongly Disagree' (1)

Appendix : B: Aman's student satisfaction questionnaire

Question		Answer
1.	How comfortable are you with online learning technology?	◦ Very uncomfortable with online learning technology ◦ Uncomfortable with online learning technology ◦ Neutral ◦Comfortable with online learning technology ◦ Very comfortable with online learning technology
2.	A clear introduction (including overall design, navigation and faculty information) was available at the beginning of this on-line course.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
3.	Technology support was available for using online features of this course.	◦◦ Strongly Disagree Disagree ◦ Neutral

Question		Answer
		◦ Agree ◦ Strongly Agree
4.	Student support (for example, advising, financial aid, registration) was available in using the online format of this course.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
5.	I find it important to be provides with the learning objectives of a course.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Disagree
6.	The objectives for this online course were provided at the beginning of this course and were clearly described.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
7.	The course objectives for this online course were closely related to what I was expected to learn.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
8.	The course objectives for this online course assisted with guiding my learning activities.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
9.	I find it important to be provided with the course assessment methods at the beginning of a course.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
10.	The course assessment methods for this online course were provided at the beginning of the course.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
11.	The course assessment method for this online course were clearly described.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦Agree ◦ Strongly Agree
12.	The course assessment methods for this online course included a variety of assessment methods.	◦◦ Strongly Disagree ◦ Disagree Neutral

Question		Answer
		◦Agree ◦ Strongly Agree
13.	The course assessment methods for this online course were closely related to the course objectives.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
14.	I find it important to be provided with course resources and materials during a course.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
15.	The course resources and materials for this online course were easily accessible during the course.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
16.	The purpose of course resources and materials for this online course were clearly described.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
17.	The course resources and materials for online course helped me reach this the course objectives.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
18.	The course resources and materials for this online course included a wide variety of resources and materials.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
19.	I find it important to interact with the instructor during a course.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
20.	The course instructor for this online course interacted with me in a timely fashion.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
21.	The course interaction with the instr-uctor for this online course helped me reach the course objectives.	◦◦ Strongly Disagree ◦ Disagree Neutral

Question		Answer
		◦ Agree ◦ Strongly Agree
22.	The amount of course interaction with other students for this online course was helpful in reaching the course objectives.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
23.	I find it important to be provided with course technology that enhances learning during a course.	◦◦ Strongly Disagree ◦ Disagree Neutral ◦ Agree ◦ Strongly Agree
24.	The course technology for this online course was readily available during a course	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
25.	The course technology for this online course was functioned very well.	◦◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
26.	The course technology for this online course was helpful in reaching the course objectives.	◦ Strongly Disagree Disagree ◦ Neutral ◦ Agree ◦ Strongly Agree
27.	What's your gender?	◦ Female ◦ Male
28.	How many online courses have you taken in the past? (enter a number)	
29.	What's your age (optional)?	
30.	Overall, I'm satisfied with this online course.	◦ Strongly Disagree ◦ Disagree ◦ Neutral ◦ Agree Strongly Agree

Declarations

Data and Ethics Participation data was collected anonymously. Appropriate permissions and ethical approval for the participation requested and approved. Anonymous quantitative and qualitative analyses results are accessible upon request.

Conflict of Interests There is no potential conflict of interest in this study.

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