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ORIGINAL ARTICLE

Intelligent personalised learning system based on emotions in e-learning

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Abstract

One of the greatest challenges in the success of a personalised e-learning system lies in the behaviour identification of the learners during the learning and evaluation phase. The content delivery in an e-learning system must be modified and updated periodically according to the preference and behaviour of the learners. Usually, the behaviour of the learners drastically changes according to their affective states during the learning phase. The accurate identification of the learner's negative emotions and addressing such emotions carefully in a positive sense can greatly provide success to the learners. In this paper, the learner's emotions especially frustration emotion are automatically and accurately estimated using the information received from learning management systems (LMS) using the Takagi sugeno fuzzy inference engine. Based on this estimation, several motivational messages are distributed according to the identified emotions which had greatly helped them to succeed during e-learning. The motivational messages that are used for sending to the learners are based on regulatory fit theory. Several kinds of statistical tests are used in this paper for deep analysis. Two sets of learners, namely, control and experimental sets, are identified from undergraduate students. Experimental results are shown for these two sets to reveal the increase in their emotional strength after receiving the motivational messages. Statistical analysis *t*-test is also applied to the two sets, and the experimental results have shown that there is a significant difference between the two groups which shows the dominance of the proposed system.

Keywords Emotions · Sugeno fuzzy inference engine · Regulatory fit theory · E-learning · Frustration

1 Introduction

Instructors and students in higher education have been profoundly impacted by the rise of information and communications technology (ICT). Using technology-based learning systems such as learning assistance tools, instructors, and technical resources can help students acquire information and skills [1]. A pandemic has made it even more important for these systems to support instructors as they rethink and change the learning design of their courses in order to provide students with more meaningful learning experiences. With the help of these tools, students can become more involved in their own education [2, 3]. Learning management systems (LMS) such as Blackboard, Moodle, and

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Canvas are currently the most popular options for students. There are numerous benefits to using these systems that include consistent availability and accessibility of course contents, cost benefits, collaboration between students and instructors, enhanced performance through student feedback, and effective communication.

By distributing content online and including additional components like quizzes, slideshows, screencasts, assignments, and forums, learning management systems can help students learn more effectively. In addition, LMS make the process of distributing and administering these resources a breeze for instructors [4]. Students' online behaviour may be examined and used to enhance teaching and learning in an LMS and massive open online courses because every action is recorded and kept [5]. Moodle (modular object-oriented development learning environment) is an open-source online learning management system, which is being used free by hundreds of millions of students around the world.

Students get enrolled in different courses. Students are required to read course materials, take part in a discussion forum, and pass multiple tests over the course's duration. Student interactions are recorded in Moodle's log file. In the end, it generates enormous amounts of data. Information about user behaviour is stored in log files generated by learning management systems (e.g. course view, resources access, assignment submission, project submission, evaluation of assignment and project, quiz, and forum interaction). For example, this data was utilised to predict student performance, detect procrastinators, and group people into categories. This information can be found in the log files of students who use learning management systems [6].

Students' abilities and skill attainment are taken into account when adaptive learning systems are developed to dynamically modify the level or kind of course content. In order to do so, these adaptive systems help to handle issues, namely, student learning abilities, diverse student backgrounds, and resource limits. Learning outcomes and skill mastery are the ultimate goals of these computer learning systems, which employ proficiency to determine what a student really knows and to progress students along a sequential learning route with accuracy and rationale. Students can track their own progress through the systems' automatic feedback cycles, giving them greater autonomy over their own learning. In addition, as described in [7], learning styles have a significant impact on student success. Learning style prediction is a difficult task since learner's behavioural data is uncertain in nature. Fuzzy rules are proposed as a way to address uncertainty in learning style predictions, especially in web environments [8].

Using artificial intelligence (AI) in education has opened new avenues for the development of more effective technology-enhanced learning tools. It is important to consider the sort of data that will be used and how it will be analysed in order to make inferences about certain features when adopting a user modelling technique or approach. Fuzzy logic was developed as a way to compute with words [9]. Fuzzy logic is a type of multi-valued logic that allows for intermediate values between binary values such as yes/no, high/low, and true/false. Concepts such as being fairly tall or very fast can be analytically defined and addressed by computers in order to adopt a more human-like approach to computer programming. Several studies have successfully integrated a fuzzy logic into the ITS learner model. Fuzzy logic was utilised to estimate the level of understanding of a learner [10].

1.1 Basic problem

The Academic Self Efficacy Beliefs Questionnaire (ASEBQ) [11] and Motivated Strategies for Learning Questionnaire (MSLQ) [12] are used for assessing a learner's Academic Self-Efficacy (ASE) and Task Value (TV). ASEBQ is preferable than others since it categorises the items into the following four groups: (1) self-efficacy in academic performance outside of class; (2) self-efficacy in academic performance in class; (3) self-efficacy in classroom interaction; (4) self-efficacy in capacity to balance work, family, and school. MSLQ is designed to examine the students' value beliefs for a course. A wide variety of psychometric questionnaires are used to evaluate psychological qualities. For example, questionnaires such as the ASEBQ and the MSLQ are used to assess the academic self-efficacy and task value, respectively. Moreover, this might be used to quantify the emotions (based on control value theory) evoked by an achievement.

1.2 Extended problem

The drawbacks of using questionnaires to gauge students' levels of emotion are listed as follows: (1) self-reported inaccuracies such as dishonest answers, (2) a lack of thoughtful responses, and (3) questions that were misunderstood or misinterpreted can skew the results. In addition to this, survey analysis must be revised multiple times during the experiment since student's emotional and motivational characteristics change over time. Control value theory emphasises self-efficacy and task value in order to assess the emotions connected to a learner's sense of accomplishment. Moreover, control value theory classifies the emotion into three classes, namely, retrospective (after a success), activity (during an achievement-related activity), and prospective (before the success).

The work by [13] describes the analysis of an individual's self-efficacy during the learning phase in order to foresee possible emotions. Self-efficacy and task value are regarded to be the two most influential components in forming an individual's achievement emotion. Recognising these LMS learning habits enables instructors to address the e-learner's emotional state by offering customised instructions based on their level of self-efficacy and task value. The proposed fuzzy systems demonstrated good results for measuring academic self-efficacy and task value, which can be utilised to determine potential outcome emotions.

1.3 Novel problem

Understanding how people receive, absorb, and process information is a significant challenge in education. Learning is not just a cognitive activity; it is also influenced by human emotions. A person's emotional condition has an impact on his or her ability to learn. This research work focuses on collecting the learner's behavioural data from Moodle. Next, the prominent features are extracted and grouped using exploratory factor analysis. This proposed work focuses on detecting the activity emotion, frustration based on the control value theory. The age group of learners varies from 17 to 21. Under this age group, the learners undergo mood swings during their course of study. Moreover, the learners undergo stress due to various factors such as heavy workload, environmental impact, hormonal imbalance, and diet. This stress leads to frustration which affects the performance during the learning phase. Hence, frustration emotion is considered in this research work. Fuzzy inference system is used to predict the emotion of the learner. This inference engine calculates the stress value of the learner during the learning phase. External pressures that exceed the learner's capacity for adaptation may result in stress, a state of emotional provocation. Numerous studies have been conducted to determine the effect of academic stress that the learners experience during their learning phase. Learner's academic performance has been shown to be inversely associated with stress. This stress value indicates the frustration level of the learner. Based on the frustration level, gain frame motivational messages based on regulatory fit theory are delivered to the learner. Moreover, statistical analysis on emotional intelligence before and after receiving the motivational message was done.

The motivation for this proposed work arises due to the following scenario. The average performance of the students in a class varies in different assessment tests of a particular semester. The geometric mean of the students in the class differs in various time intervals. For example, the average performance of a class is 80% in the first assessment, and it reduces to 40% in the second assessment. Emotions play a major role for the variation in academic performance. Hence, the major contribution of this research work for the novel problem is as follows. The comparison between the basic problem, extended problem, and novel problem is given in Table 1.

- To estimate the activity emotion, frustration during the learning phase precisely using intelligent techniques.
- To efficiently predict and verify the input parameters for emotion estimation statistically.
- To provide exploratory factor analysis-based mathematical modelling for input parameter estimation.
- To effectively deliver motivational messages based on emotions during the learning phase.
- To provide a comparative analysis of emotional intelligence during the entire learning phase.
- To statistically compare the performances of the learners before and after the delivery of motivational messages during the testing phase.

The remainder of this manuscript is organised as follows. Section 2 discusses prior works by various authors, while Section 3 discusses the proposed system architecture for emotion prediction using the Takagi-Sugeno fuzzy inference system followed by the delivery of gain frame motivational messages using regulatory fit theory. Section 4 gives the performance analysis of the implemented fuzzy system, and Section 5 concludes this work.

2 Related works

The learning process can be accelerated by recognising and responding to the learner's emotional state. The previous works in the literature identify the key factors for an effective learning experience which include motivation, self-confidence, risk-taking behaviour, academic interest, and creativity [14, 15]. In order to get the most out of online and remote learning, Santhanam et al. [16] looked at how students' emotions may be assessed. E-learning platforms allow students to study and learn at their own pace; therefore, self-regulation of motivation and behaviour is required during the learning phase in this learner-centred platform.

Anderson et al. [17] classified learner's engagement into different categories. The first category behaviour refers to the active participation of the learner to engage in learning activities such as attending the course regularly, active participation in discussions, submitting the assignments on time, and following instructions given for completing the course. The next category of learners may successfully complete their allotted work while being dissatisfied or annoyed/frustrated with it. This refers to a student's emotional reaction to learning. Students are highly motivated to learn yet have a low level of emotion to complete the work. The final category refers to the process of learning in which a learner's cognitive talents, such as concentration and innovative thinking, are completely utilised.

Many e-learning systems are now focusing on e-learning environments that are tailored to the learner's emotional condition. Affective state detection helps educators to identify the learners who lack motivation to show progress in their performance. Affective state detection research aims to establish a link between a person's emotional state and the data that can be gathered about them from various

Table 1 Comparison of basic problem, extended problem, and novel problem

Problem	Reference	Advantages	Disadvantages
Basic problem	A. Zajacova, S. M. Lynch, and T. J. Espenshade [11]	Evaluates learner's motivational impact through questionnaire	Does not prove to be successful in predicting the emotions
Extended problem	Z. Karamimehr, M. M. Sepehri and S. Sibdari [13]	Predicting prospective emotions using fuzzy logic	Does not deliver motivational messages based on the emotions predicted
Novel problem	-	-Predicting activity emotion using fuzzy inference system -Delivers motivational messages -Emotional quotient and assessment evaluation before and after delivery of motivational messages	-Does not include learning style -Need to consider various emotions during learning phase

sources. Sensors and equipment of many kinds are used to gather data that can be utilised to make inferences about emotional responses based on facial expressions, bodily movement, and multimodal techniques [18–23]. There are, however, a few drawbacks to employing these devices, including high costs and low-quality input channels. Emotions detected by sensors are short-lived; therefore, their applicability will be limited to the emotions felt during the activity. As a result of these factors, several research have attempted to predict the emotions and other personal traits of learners in learning portals based on their behaviour [24], which has proved to be efficient than sensor-based detectors. According to Conati and Maclaren [25], adaptive learning systems based on affective state can boost intrinsic motivation, leading to more concentration in learning over a certain length of time.

A probabilistic model for forecasting the joy/distress towards an event was developed by [26]. Students' goals, personality, and knowledge were also taken into account when determining their perception of the game's impact. Participants' initial knowledge level and click-through behaviour were used in a model for evaluating their confidence level in an instructional game developed by Katsionis and Virvou [27]. Deleted/corrected answers were used to gauge a student's confidence level, and aimless mouse movements were utilised to gauge a student's focus and annoyance levels. There were five specialists in the field who analysed the data and put down what they thought the learners would have felt.

While it may be easy to distinguish emotions in an e-learning environment, it is difficult to identify those that are linked to learning. Using a concept from the control value theory (CVT) and a probabilistic relational model, Munoz et al. [28] attempted to explain the learner's mood. The authors [29, 30] considered the students emotions (e.g. joy, anxiety, and frustration) as a significant predictor of their accomplishment level. Emotions during online learning have been extensively researched in the literature. For example, enjoyment has been shown to be positively associated with the student's exam performance, whereas frustration has been shown to have a detrimental effect on the student's learning and task value. This results in neglecting/denying to acquire new knowledge acquisition [31, 32].

Zahra Karamimehr et al. test a nonsurvey-based technique for characterising student emotions in their research work. To determine the emotional state of an e-learner, instead of surveys, data gathered through LMS were used. Control value theory (CVT) is the theoretical foundation of this work for measurements of emotions. Using this hypothesis, students' feelings are closely linked to their success. In order to quantify academic self-efficacy (ASE) and task value, two fuzzy inference systems, ASEMEL and TAVAMEL, were created. According to the CVT, these two criteria can be used to predict future emotional responses in a learning setting. A sample of 30 students was used for the experiment on an LMS, and the results were validated by comparing them to the results of an equivalent survey-based method.

According to Ashley O'Connor et al. [33], motivating messages for patients can be created using regulatory fit theory. This will help them adhere to their drug regimens better. Adopting the regulatory fit theory into message initiatives can assist in health care communications. As a result, stronger patient-doctor interactions can be established. In addition to this, better communication about the need of adhering to medical orders will ensue. Tze Wei Liew et al. [34] motivated students in online learning environments by utilising inspirational messages supplied by virtual agents. This research work examined the message frame of an e-learning virtual agent to evaluate whether it has an effect on learners' cognitive load and self-motivation. When a virtual agent was utilised to enhance learning, it was revealed that using a gain-frame message was beneficial in modifying students' behaviour.

Amy E. Latimer et al. [35] investigated whether gain frame or loss frame messages targeted to people's promotion- or prevention-oriented goals evoke positive thoughts and sentiments about doing exercises and improve their body health. Participants who are not active were randomly assigned to receive either gain frame or loss frame messages to motivate their participation in the activity. The authors investigated individuals' attitudes and feelings regarding physical exercise and physical activity behaviour after delivering the messages. Personalised gain frame messages that matched individuals' regulatory priorities resulted in increased physical activity engagement and good feelings compared to loss frame messages. The impact of gain frame messages resulted in participant's active participation in their daily exercise routine and created awareness in their body health.

Nimala K. et al. [36] proposed a new method of determining sarcasm prevalent topics based on the sentimental distribution among the short text and to some extent contribute to sarcasm detection using an unsupervised probabilistic relational model in machine learning. This model figures out and detects sarcasm and sarcasm prevalent topics that clearly understand the fact and context of the particular related event. But this will suit for only short text, not for longer sentences, which is of a special need nowadays. Aslam et al. [37] proposed the importance of the e-learning process and different types of pertinent e-learning features and evaluated the performance with machine learning algorithms. Vivekananthamoorthy N et al. [38] have created an experimental-based e-learning website which is useful for students to find the learning materials and they can easily interact with staff to satisfy their learning prerequisites. Finally, they have proved SNS (Social Networking Sites) and eWOM (electronic Word of Mouth) statement as influential power in e-marketing.

Previous works in the literature focused on using sensors for monitoring the body movements, facial expressions etc. in order to predict the emotional state. In addition to this, survey-based methods using questionnaire and fuzzy system (non-survey-based method) were also used to predict the learner's emotional state. This research work focuses on extracting the learner's behavioural data from LMS. The Takagi-Sugeno fuzzy inference system is used to predict the stress value of the learner during the learning phase. If the stress value exceeds the threshold value, the learner is in frustration. Based on the frustration level of the learner, gain-frame motivational messages are delivered to the learner. Moreover, the emotional intelligence value is calculated before and after the learning phase and proved that the emotional quotient and the learner's performance are improved through statistical analysis.

3 Proposed work

The system architecture for predicting the emotional state of the e-learner in an e-learning environment is shown as the novel problem in Fig. 1. The basic problem in the system architecture depicts that the emotions of the learners were predicted through the questionnaire ASEBQ and MSLQ. Next, the extended problem predicts the prospective emotions based on control value theory automatically through fuzzy systems. The proposed work focuses on the novel problem to predict the activity emotion, frustration, and send motivational messages to the learners. Moreover, this research work focuses on both emotional quotient and assessment evaluation before and after the delivery of motivational messages. Learners use Moodle as a Learning Management System (LMS), to perform the learning activities such as learning the course content, doing assignments, projects, assessments, and interact in a discussion forum.

The learner enrols for the course after completing the registration. Next, learners study the course materials, interact in discussion forum, and complete various exams during the course duration. Meanwhile, instructors can make announcements, grade assignments, monitor course activity, and join class discussions. While interacting with the LMS, learners perform different types of activities. The database stores all sorts of activities and interactions performed by the learners from which information about learners' characteristics and learning behaviour may be extracted. Moodle keeps track of learner interactions during the course via a log file. Learners learning behavioural data are collected from the Moodle system's log file.

3.1 Feature extraction

Feature extraction is more important before moving on to the analysis of Moodle log files. Moodle log contains the complete log history of the learner which records the different activities performed by the learner during the learning phase. The optimal features required for analysis of this work are extracted from the Moodle log files. The purpose of feature extraction is to improve the quality of the data and to extract the optimal features for the selected analysis. The abbreviation of features used for the analysis along with its description is given in Table 2. A 5-point Likert-type scale of 1 (not related at all) to 5 (extremely related) was used to score the intensity of each LMS behaviour's relationship to each stress dimension to determine the most effective LMS behaviours for dealing with stress. Here, we focus on stress since frustration is an emotional response to stress. Then, we conducted a binomial statistical test with a test proportion of 0.5 and set the

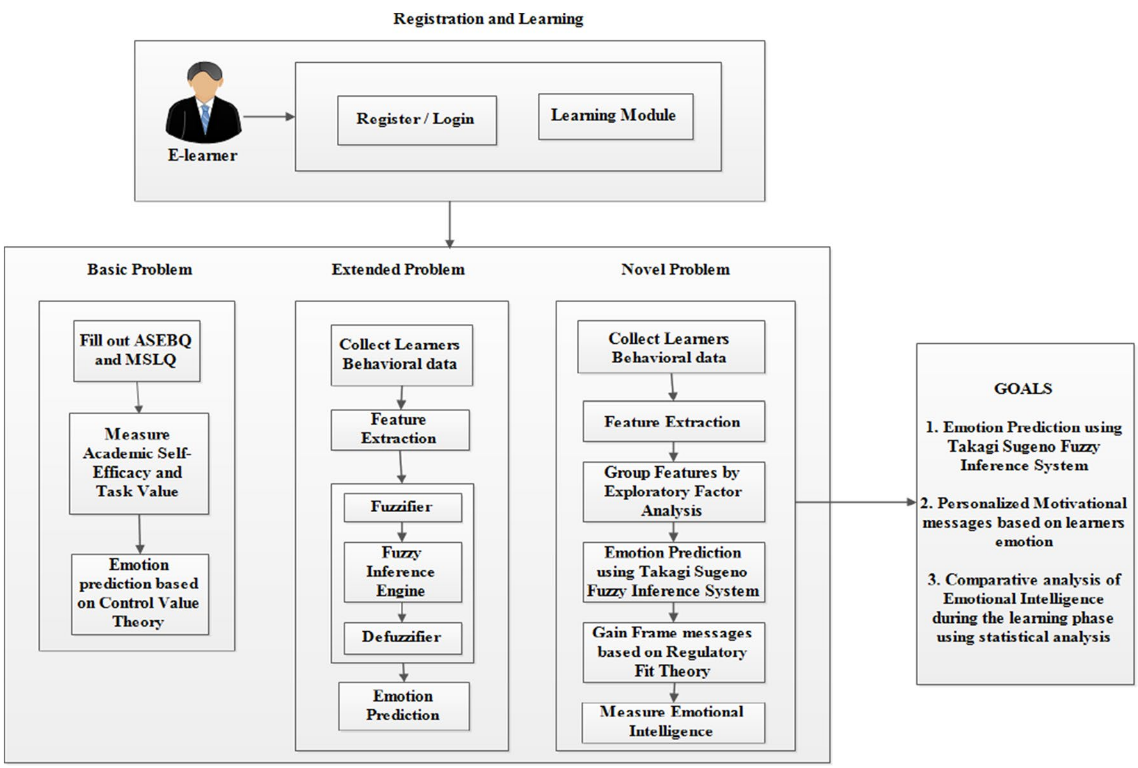

Fig. 1 Proposed system architecture

threshold as 3. The learner's LMS behaviours with the threshold value more than 3 were chosen, while the remaining were eliminated. Thus, the associated LMS behaviours as shown in Table 2 were identified using a binomial distribution.

3.2 Group features using exploratory factor analysis

The main aim of factor analysis is to investigate the relationships between a large number of variables and check whether they can be grouped in terms of common underlying factors. Exploratory factor analysis (EFA) [39] was conducted for the LMS behaviours extracted from log files. The LMS behaviours were framed as a questionnaire and given to the learners to rate them in a 5-point Likert-type scale of 1 (strongly agree) to 5 (strongly disagree). The mean, standard deviations, skewness, and kurtosis of the questionnaire items were examined using IBM SPSS Statistics version 23. In order to determine whether the sample size is adequate, the KMO test of sampling adequacy is used. If the KMO value is closer to 1, then it is reasonable to conduct factor analysis or else it is not acceptable to conduct the factor analysis. Bartlett's test of sphericity checks whether the data has adequate correlation. EFA suggested a three-factor solution for the ten LMS behavioural data. The first factor denotes the activity outcome (AO), the second factor denotes the interaction outcome (IO), and the third factor denotes the learning outcome (LO).

Table 2 Features along with its descriptions

S. no	Feature	Description
1	TLCC	Time spent for Learning the Course Content
2	UCC	Understanding the Course Content
3	FCSC	Following Course Schedule Correctly
4	RDCC	Raising Doubts in Course Content
5	RQCC	Response to Questions asked in Course Content
6	APGA	Active Participation in Group Assignment
7	ASD	Assignment Submission within Deadline
8	APDF	Active Participation in Discussion Forum
9	ACQR	Attempting Class Quiz Regularly
10	ALEPD	Average number of Log Entries Per Day

3.3 Emotion prediction using fuzzy inference engine

The LMS behaviours pertaining to learning outcome are TLCC, UCC, and FCSC. Similarly, interaction outcome includes RDCC, RQCC, and APDF; activity outcome includes ASD, APGA, ACQR, and ALEPD. For fuzzy systems, the crisp input variables must be converted to fuzzy linguistic variables. In order to accomplish this, the lower and upper bound value is identified for each feature extracted. To convert the crisp input to fuzzy input, a trapezoidal membership function is used. The linguistic variables associated with this conversion process are “high”, “moderate”, and “low”. For example, if the learner attempts the class quiz less than three times, then ACQR is low. If the learner attempts the quiz three to four times, then ACQR is moderate, and for greater than four, ACQR is high.

Initially, a fuzzy system is used to predict the value of learning outcome, interaction outcome, and activity outcome with the rule base given in Table 3. A fuzzy inference system (FIS) incorporates the expert’s knowledge to build a fuzzy system. The rule base consists of IF–THEN rules as shown in Table 2. This research work uses the Takagi-Sugeno fuzzy inference system (TSFIS) [40] where the system takes fuzzy inputs and produces the weighted average crisp output. This crisp output is the linear combination of inputs. The format of the TSFIS fuzzy rule is as follows:

IF x is A and y is B THEN z is $f(x, y)$

where x and y are inputs, A and B are fuzzy sets, and $f(x, y)$ is a mathematical function.

The output is defined as given in Eq. 1

$$z = \frac{\sum_{i=1}^{k} w_i z_i}{\sum_{i=i}^{k} w_i} \tag{1}$$

where w_i represents the weights, z_i represents the output of each rule, and k represents the number of rules.

Emotion prediction using the Takagi-Sugeno fuzzy inference system is shown in Fig. 2. Fuzzy inference is a procedure that uses fuzzy logic to derive new knowledge from current knowledge. This process of defining the mapping from a given input to an output establishes a foundation for decision-making and pattern recognition. The first stage in designing a fuzzy expert system is to define the input and output parameters. After describing the fuzzy variables and membership functions, the if-then fuzzy rule base may be defined as given in Table 4. The amount of fuzzy rules defined is dependent on the membership functions that can be combined. FIS with n-input variables use the $k = m^n$ rule set, where m is the number of linguistic phrases contained in each input variable. The size of the rule base grows exponentially as the dimension and complexity of a system increases.

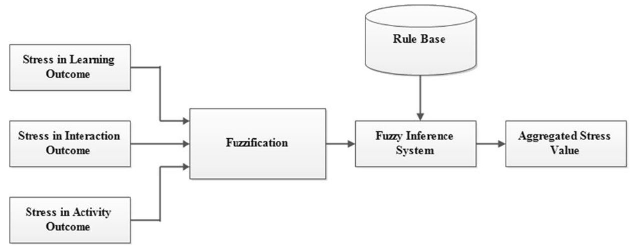

Fig. 2 Emotion prediction using the Takagi-Sugeno fuzzy inference system

The stress value of learning outcome, interaction outcome, and activity outcome is given as crisp input to the system. The crisp input is converted to fuzzy input with linguistic variables low, medium, and high during the fuzzification process. Next, with help of the rule base, fuzzy inference system finds the aggregated stress value using Eq. 1. If the calculated stress value exceeds the predefined threshold value, then the learner is in frustration during the learning phase.

3.4 Regulatory fit theory

Each and every individual learner looks the world in a different perspective. Based on their perspective, learners can be grouped into two categories. The first category of learners works towards the positive outcome of the goal, and the second category works to avoid the negative outcome if the goal is not achieved. A learner’s attitude towards a particular behaviour is positive if they believe it will result in something they value. Changing behaviour becomes more appealing when one has a positive attitude on it. Attitudes are shaped by the behavioural ideas that each learner holds and the weight

Table 3 Sample rules for predicting learning outcome, interaction outcome, and activity outcome

Factor	Rules
Learning outcome (LO)	If TLCC is high and UCC is moderate and FCSC is high, then LO is high If TLCC is low and UCC is moderate and FCSC is low, then LO is low If TLCC is moderate and UCC is moderate and FCSC is high, then LO is moderate
Interaction outcome (IO)	If RDCC is low and RQCC is moderate and APDF is low, then IO is low If RDCC is high and RQCC is high and APDF is moderate, then IO is high If RDCC is high and RQCC is moderate and APDF is high, then IO is high
Activity outcome (AO)	If ASD is low and ACQR is moderate and APGA is low and ALEPD is low, then AO is low If ASD is high and ACQR is high and APGA is moderate and ALEPD is high, then AO is high If ASD is moderate and ACQR is moderate and APGA is low and ALEPD is moderate, then AO is moderate

Table 4 Sample rules to calculate stress value

Output	Sample rules
Aggregated stress value	If LO is high and IO is moderate and AO is high, then stress is low If LO is low and IO is moderate and AO is low, then stress is high If LO is moderate and IO is moderate and AO is high, then stress is moderate

they place on those beliefs. When a learner associates specific features, characteristics, and events to certain behaviours, he or she has behavioural beliefs. How strong a belief has an impact on one's attitude relies on the belief itself and how strong the belief is considered to be by the individual learner. The way a message is framed may have an impact on learner's attitudes and, as a result, their desire to alter their behaviour. A message's presentation can have a significant impact on how it is interpreted by the learners.

According to regulatory fit theory, two unique goal-seeking orientations exist, each with its own particular motivational effect [41]. On the one hand, a desired end state can be articulated as a wish, hope, or aspiration. Moreover, ideal self-regulation is oriented towards promotion, whereas essential self-regulation is oriented towards prevention. For example, a person with a promotion attitude would eagerly wait for the class sessions, assignment, and quiz and would emphasise on the benefits of learning. Meanwhile, someone with a preventive attitude would avoid doing not to skip assignments or quiz out of fear associated with inactivity. The messages framed can be either gain-frame or loss-frame messages. It is important to achieve positive outcomes or avoid negative repercussions while communicating with a gain-frame message. A loss-frame message, on the other hand, emphasises the possibility of suffering a negative outcome or failing to achieve one's goals.

In this research work, the learner's stress value is predicted using TSFIS. Based on the stress value, the frustration level of the learner is known. Now, if the frustration level exceeds the threshold value, gain-frame messages are sent as feedback to the learner. The motivational impact of learners during the learning can be greatly improved with the help of gain-frame messages. Previous works [42, 43] performed experiments for classification task on both promotion focus and prevention focus and concluded that promotion focus participants outperformed when compared to prevention focused participants.

There is a strong correlation between the learning process and regulatory fit theory. Promotion-focused learning strongly influences the learning process and its corresponding outcome. The gain frame messages mainly focus on the merits of performing well in the course by doing all the assignments correctly, attending quizzes properly, raising questions, and active participation in discussion forums, etc. during the learning phase. The use of gain-frame messages, which highlight the rewards associated with reaching a learning objective, may be effective for motivating the e-learner's learning behaviour. The gain frame messages are more successful when compared to loss frame messages. Hence, this work focuses on gain frame motivational messages which help the learner to enhance his performance in the future.

4 Performance analysis

Participants were studying second year in the Computer Science and Engineering department at the University College of Engineering Tindivanam. Forty-three participants (13 female and 30 male) were registered for the Data Structures course in Moodle. The participants/learners were divided into two groups, namely, the control group and the experimental group. The control group learners will not receive gain frame messages, whereas the experimental group learners will receive the gain frame messages.

4.1 Parameter selection

During the feature extraction, the probability for selecting each parameter from the set of extracted LMS learning behaviours should be equal. The probability for selecting each feature is the same, and the likelihood for each feature is either to be selected or not selected. The probability of selecting a feature does not depend on the selection of other features. Hence, each feature extraction is independent, and this fits to the binomial probability distribution $B\,(n, p)$ given in Eq. 2 [44].

$$p_{n(k)}=\binom{n}{k}p^{k}(1-p)^{n-k} \tag{2}$$

4.2 Exploratory factor analysis

Exploratory factor analysis (EFA) is a statistical approach to uncover the structure of a larger number of features in multivariate statistics. The large number of observed features is considered to be connected to a smaller number of "unobserved" factors. To uncover the underlying factors from the observed LMS learner's behavioural data, EFA was conducted using IBM SPSS Statistics version 23. Analysing the relationship between a large number of features allows determining whether they may be summarised and organised into more manageable groups by using fewer factors. Table 5 gives the results of the Kaiser-Meyer-Olkin (KMO) test of sampling adequacy and Bartlett's test of sphericity.

The KMO value is 0.826, and this denotes that the number of instances is adequate for analysis. Moreover, the significance level for Bartlett's test of sphericity is <.05. This depicts that the features extracted have enough number of correlations among them. A scree plot is used as a visualisation tool to find out the optimal number of factors for exploratory factor analysis. It shows the number of the components and its eigenvalue on a graph. The eigenvalues are arranged in ascending order of magnitude in the scree plot. This graph as shown in Fig. 3 indicates that the first three factors account for the majority of the variation in data (given by the eigenvalues). The first three eigenvalues are all greater than 1. The other variables account for only a small percentage of the variance and are probably of no significance. Hence, this concludes that the features extracted can be grouped into three factors.

Table 6 represents the amount of load that each feature places on each of the three factors after performing varimax rotation. This enables to deduce what each extracted factor may represent. Factor analysis identifies which features cluster statistically. Here, the features are grouped into three factors. Factor 1 represents the activity outcome, factor 2 represents the interaction outcome, and factor 3 represents the learning outcome.

4.3 Emotional intelligence evaluation

Emotional intelligence (EI) is a tool that helps learners make sense of their feelings and expectations when things are ambiguous. Learners have to deal with issues that they did not expect to happen during their course of study. Psychological stress impedes academic achievement. Anxiety and depression can affect students' motivation, attention spans, attentiveness, and social relationships, all of which are critical to academic success. Hence, it is important for them to display positive emotional responses to meet the academic requirements of their course of study. Stress can be exacerbated during the learning phase. In moments of uncertainty, an individual's expectations and responses are reinforced by the EI. Unpredictable events frequently occur for learners during their course of study. They are expected to exhibit positive attitudes and behaviours, such as perseverance, focus, optimism, and self-worth, in addition to achieving the criteria of their course curriculum. A person's professional and academic performance may suffer as a result of these stressful circumstances. In this scenario, EI can help learners to improve their work performance and alleviate the effects of academic stress. Initially, before starting the course, the learners in the both control and experimental groups were given the Trait Emotional Intelligence Questionnaire–Short Form (TEIQue–SF) [45].

The TEIQue–SF is a 30-item questionnaire designed to assess global trait emotional intelligence. TEIQue–SF has a Likert-style response choice structure, with response options ranging from 1 (strongly disagree) to 7 (strongly agree). The learners in both groups go through the questionnaire and rate their options value based on the questions. By adding

Table 5 KMO and Bartlett's test

Kaiser-Meyer-Olkin measure of sampling adequacy		0.826
Bartlett's test of sphericity	Approx. chi-square	5033.719
	df	45
	Sig.	.000

Table 6 Rotated component matrix

Features	Component		
	1	2	3
ASD	0.745		
APGA	0.714		
ALEPD	0.672		
ACQR	0.624		
RDCC		0.821	
APDF		0.693	
RQCC		0.647	
TLCC			0.774
UCC			0.773
FCSC	−0.498		0.554

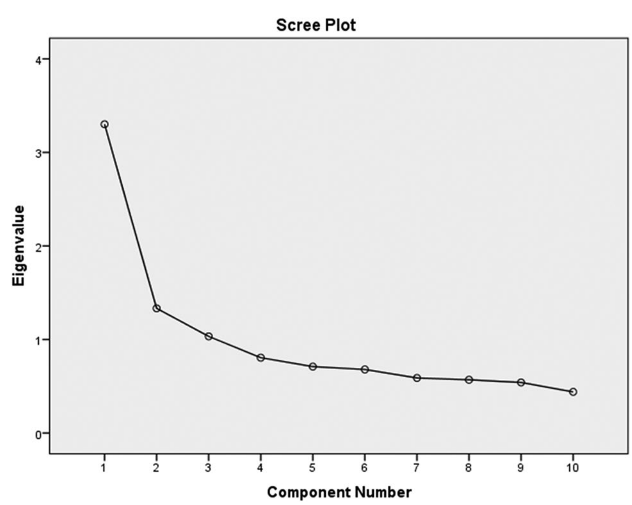

Fig. 3 Scree plot

the item scores and dividing by the total number of items, a global trait EI score is obtained. After completing the learning process, the same questionnaire is again given to control group and experimental group learners for choosing the options for the questions.

The statistical analysis was done using a paired sample *t*-test for both the control group and the experimental group separately. The emotional quotient for the learners in the control group does not have a significant difference before and after the learning phase, since the *p*-value is 0.1799. Since the learners in the control group do not receive the gain frame messages, the emotional quotient of the learner remains the same during the learning phase. The emotional quotient value comparison for the control group is shown in Fig. 4.

Now, the same *t*-test statistical analysis was done for the experimental group learners. Now, the *p*-value for this statistical test is 0.003358. Hence, this concludes that there is a significant difference in the emotional quotient value before and after the learning phase. This difference happens as the learner receives gain-frame motivational messages when he is frustrated during the learning phase. The emotional quotient value comparison before and after the learning phase for experimental group learners is shown below in Fig. 5.

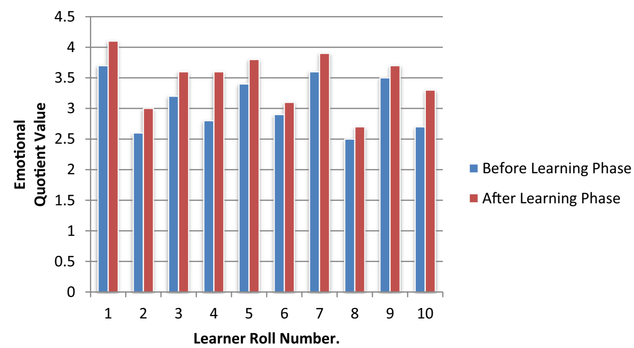

Fig. 5 Experimental group emotional quotient value

4.4 Assessment evaluation

A learner's abilities and experiences are shaped by the circumstances and environmental factors that influence their performance. The student's intellectual capacity, attitude, commitment, capabilities, passions, learning styles, and self-esteem all have a role in academic performance. Diverging performance occurs when a learner's academic achievement falls short of their projected performance. Learner's academic performance is based on their ability to exhibit their knowledge in class tests, quizzes, seminars, and the final semester examination. In an e-learning environment, learner's performance is considered to be more important since it serves as a gauge for the effectiveness of their academic efforts. Learner's attitudes, ambitions, and self-learning ability are the key factors that greatly influence on their performance.

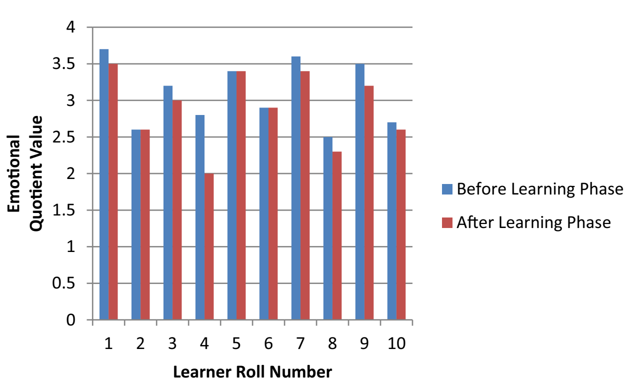

Fig. 4 Control group emotional quotient value

Participants in both the control and experimental groups take the term test for the course registered. For each semester, three assessment exams were conducted before the final end semester examination. The geometric mean for the overall class performance varies for each assessment exam. This is depicted in Fig. 6.

To succeed in their academics, the learners need to be intelligent, persistent, and attentive. Learner's mental and physical health plays a vital role in their academic success. A learner's ability to actively participate in the course registered depends on his or her physical and mental well-being. Stress, fear, trauma, depression, frustration, or other physical health issues, on the other hand, might be a hindrance to learner's academic success. In the absence of intervention, this affective state can lead to disengagement during the learning phase. In the field of computer science, it has long been a challenge to draw in new learners and keep them interested throughout their studies. There will be a gradual loss of confidence and interest in the subject matter if students are continually frustrated during the learning phase.

Hence, gain-frame motivational messages play a crucial role to improve the performance of the learners during the learning phase. This work performs the assessment evaluation for both the group of learners. The control group

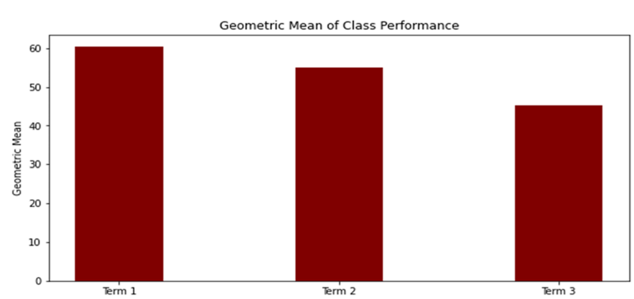

Fig. 6 Geometric mean of class performance

learners do not receive motivational message during the learning phase. For learners in the experimental group, based on the stress value calculated using TSFIS, gain-frame messages as shown in Table 7 are sent as feedback to the learners.

For example, if the stress value range is 5 to 7, gain frame message "Learning is a wonderful thing since no one can take it away from you" will be sent. If the stress value exceeds 7, then the frustration emotion is high. In such case, "Your brain possesses an almost infinite potential for learning, which qualifies you as a genius" is sent as feedback to the learner. The learners in both the control and experimental groups complete the assessment for the course enrolled after completing the learning phase. The statistical analysis using two-sample *t*-test was conducted between the two groups. The *p*-value is 0.019 which is less than the level of significance 0.05. Here, the control group learners do not receive gain frame messages, whereas the learners in the experimental group receive gain frame motivational messages during the learning phase.

The comparative analysis for performance assessment of both group learners is shown in Fig. 7. Promotional messages were found to have a more upbeat and optimistic tone, as well as it strongly focuses on the advantages of learning. This reveals that the performance is improved for the experimental group learners. Thus, emotional intelligence and assessment evaluation analysis reveal that gain-frame motivational messages motivate learners to pay attention to the e-learning course.

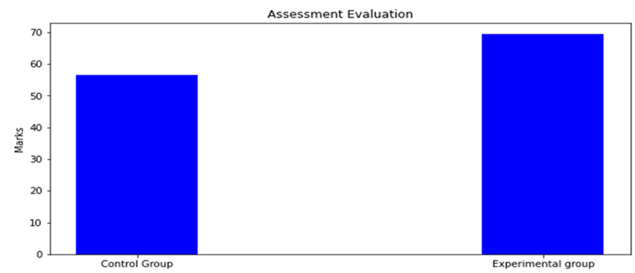

Fig. 7 Comparison of assessment marks

5 Conclusion

Predicting emotional state and identifying its source is a tremendous opportunity for the development of educational software. This research work gives importance to learner's behavioural data extracted from LMS. The input parameters were verified using binomial distribution. Moreover, the learner's behavioural data were grouped into three factors using exploratory factor analysis. Recognising these LMS learning habits helps instructors to predict the learner's emotional state using the Takagi-Sugeno fuzzy inference system. Our suggested fuzzy inference system performed well in terms of assessing stress value, which can be used to predict the activity emotion frustration. Fuzzy set theory can be used to explain the inherent uncertainty in behavioural data, providing a more realistic prediction of stress value. Moreover, statistical analysis for emotional quotient evaluation and assessment evaluation was done to show that there exists a significant difference between the learners before and after receiving the gain frame messages.

The main objective of an intelligent personalised learning system is to provide students with individualised interventions to increase their educational success in the learning system as a whole. There is still a question about how to integrate e-learners' emotional states into their pedagogical tactics, even though emotional states have been found to play an important role in the learning process of students in both traditional and online learning environments. Hence, it is important for an intelligent personalised learning system to know how effective its affective state detection techniques are and how they might be used to increase the overall efficiency of the system.

This research work does not include the parameter learning style of the learner while considering the learner's behavioural data. Moreover, various emotions apart from frustration during the learning phase need to be analysed. This proposed system was designed for a single course with a small group of learners. The future enhancement of this work is to test the

Table 7 Gain frame motivational messages

Stress value	Gain-frame messages
Moderate (5–7)	Make it a goal to learn more. If you do so, you'll never stop learning and improving The more ways you learn something, the more you understand it Learning is a wonderful thing since no one can take it away from you Daily progress adds up to major outcomes over time
High (8–10)	Your brain possesses an almost infinite potential for learning, which qualifies you as a genius Nobody can take away your ability to learn, which makes it a priceless commodity The more you read, the more you will learn. The more you learn the more destinations you will reach Nobody can assist you unless you are prepared to learn. Nobody can stop you if you are motivated to study

system on a larger group of learners, as well as for more than one course and to create scenarios that will elicit learner's emotions of various intensities during the learning phase.

Declarations

Conflict of interest The authors declare no competing interests.

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