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Affective E-Learning Model for Recognising Learner Emotions in Online Learning Environment

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Abstract— **Today online learning provides wider coverage many different approaches such as distance learning, classroom-based electronic learning and self-access learning. Online learning has been recognized as a support tool for educators and researchers simply it gives is luxury of using at anytime, anywhere. Like any learning process, online learning depends on effective communication of human knowledge, whether this occurs in a face-to-face classroom or across the Internet. Emotions can have enormous affects on learning and play a vital role in decision making, managing learning activities, timing, and reflecting on the studies. Emotions are also important in teaching and learning and often find expression in particular ways, such as interactions with others and motivation in learning. The aim of the research is to develop a computational model for recognizing leaner emotions in online learning environment. The research study was focused on developing a tool to recognise the online learner's emotions. Therefore, the study has developed Online Achievement Emotion Questionnaire (AEQ) based on the AEQ which is suited for the online learning environment. Also the study has identified a methodology for recognising learner performances during learning. That has being measured through six parameters which represent the learner's level of learning during the learning experience. These parameters are analysed using multiple regression analysis and a model equation was developed to compute the online learner's level of learning. Finally the study has analysed and evaluated the correlation between the learner emotions and the observed behaviour. This research study therefore developed a novel model of affective online learning which can be use as a tool to recognise online learner's emotions with regard to the performance in learning**

Keywords— **affective computing, e-learning, emotions**

I. INTRODUCTION

Teaching and learning via the Internet or standalone computer has opened grat avenues in the modern education system. Electronic learning is essentially the network-enabled transfer of skills and knowledge by the online facilitators to the online learners. The development of the information and communication society, which marks the current global and competitive environment, gave rise to exceptionally dynamic changes [1]. At present the online learning has becomes one of the most state-of-the-art expressions of delivery methodologies in higher education system [1], [2]. Recent research in higher education shows that there is a greater increment of e-learning courses compared to conventional educational programmes [3], [4].

Adult learners may face lot of challenges in teaching and learning, passing examinations and becoming well educated persons. Most of the problems faced by the learners are common to both online learning and face to face learning. Feedback is one of the key aspects of effective learning and learners' greatly value feedback on the learning performances due to getting individual attention [5]. The conventional large scale face to face learning does not adequately facilitate the provision of feedback on the learner performances. One missing factor of such learning environment and e-learning is recognising the learner behaviour during the learning session.

Emotions arise from memories and reactions to current events of a human being it has been addressed as one of the most controversial topics in psychology and plays a vital role in human learning process.

E-learning has been depicted as less emotional and more impersonal or as lacking in emotional richness due to not recognition of body language, facial expressions, and gestures of the users or learner when compared to face-to-face learning [6]. Online learning systems are not willing to provide real time feedback to the learner due to many reasons. These reasons sometimes clashes with the learning objectives such that the learner does not get the benefit of getting the actual feedback of learning performances during the learning process. The learner's emotions have a great impact on the learner motivation towards better learning.

II. RESEARCH PROBLEM

Adult learners especially prefer to have more freedom in the learning phase [7]. One of the major problems in the online and distance learning is the lack of methods to recognise learner behavior during learning. Therefore, the current study addresses the problem of recognizing e learner's emotional state during learning. Although, most of the researchers studied about online learning concepts, there is a lack of a study on how learning performance reflect the emotional status of e-learners of online learning in higher education. This research model will help to identify e learner's emotional state with respect to their level of learning. The research question of this study therefore is, "Do the learning performances reflect the emotional status of e-learners in the present setting of online learning in higher education?"

III. AIM OF THE RESEARCH STUDY

The aim of the research study is to develop a computational model to recognise learner emotions in an online learning environment. The proposed e learning model will address the issue of not recognizing and responding to e learner's emotions while they learn. This model will also be helpful to identify the e learners' learning performances while measuring the emotional state.

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IV. The Research Design and Architecture

This research study was primarily focused on building a computational system, which can identify the user's emotional state and react accordingly in the learner management system. Therefore the main aim of this research study is to develop an affective e-learning model that could be adapted to suit the emotions of individual learner.

The combination of technology enhanced learning and affective computing can be applied to the online learning community. The research study focuses on building the relationships among affective computing concepts and methodologies in line with e-learning. The association between affective computing techniques and online learning approaches will produce a novel approach of affective e-learning model. In-order to develop the model various elements of the learning pattern of the learners will be captured in order to measure the learner performances.

The system architecture of the research will help to identify e-learner's emotional state with respect to their level of learning. The computational model has been designed based on the system architecture which enables the novel research model to identify the e-learners' learning performances during the studies while measuring their emotional state. The basic architecture of the system consists of different research modules. The first module described in the system architecture elaborated on how the existing online learner interact with the system and how different performance based activities are taking part in the online learning environment. The second module described the novel approach of online learning which consist of couple of sub modules. The first sub module elaborates on how online learners' emotions can be captured during learning which is named as emotion library module. The other sub module illustrates on how the learner performances can be evaluated during the learning activity. Both emotion library module and learner performance module merges together and creates the novel approach of affective e-learning model.

V. Research Methodology

In exploring the affective model in online learning it was decided to carry out a user study questionnaire based emotion analysis. This study adopted an experimental based approach in measuring, testing and validating the current e-learning system. Finally, this exploratory research and empirical study will be developed using the affective e-learning model based on Kort's [8] affective learning model. The affective e-learning model uses different parameters to measure the learning level of the online learner and it will be evaluated at the end of the learning process. The parameters have been selected based on the evaluations of the three sub modules of the existing online learning environment. Therefore the observable measurements have been identified as the parameters of the level of learning without disturbing the learner physically. Also the study will be discussed in detail, including the methods used for data collection, analysis, and validation. The methodology of affective e-learning model will be described in two distinct parts which will measure the learners' emotions and measure the learner behaviour. The combination of the two models will be the result of the affective e-learning model.

A. *Measuring learner emotions*

Research on the emotions of online learning also emphasizes the importance of affective dimensions in online learning and maintains that the full promise of web-based education will not be realized, unless affective aspects are properly acknowledged [9]. Emotions are important in adult learning because they can either obstruct or motivate learning. Moreover, recent research on the emotions of online learning has focused on the importance of learners' feelings in relation to the sense of community of learning.

Achievement emotions have a direct impact in learning situations on achievement activities and achievement outcomes [10]. The research study have selected the Achievement Emotions Questionnaire by Pekrun in order to build the tool for recognize learner emotions is online learning. Previous research studies on achievement emotions were typically focused on emotions related to achievement outcomes such as anxiety, pride, or shame linked to success and failure [10]. The AEQ has used the definition of academic achievement emotions pertaining to achievement-related activities such as enjoyment of learning, boredom experienced in writing assignments or anger at the difficult assessments and tasks [10].

B. *Designing of online AEQ*

The Online Achievement Emotions Learning Questionnaire has been designed based on AQE. It was developed as a multidimensional self-reporting instrument to assess the achievement emotions of the online learners in higher educational context based on the state education system in Sri Lanka. Both qualitative and quantitative approaches have been used in the analysis of data to generate the results. The original form of AEQ was developed in the context of higher education based on class room teaching environment consequently in this research AEQ was modified to match with the online learning environment. The tool often can be called as "Online AEQ" which measures a number of discrete emotions for each three main academic situations that engage in LMS, learning online and facing test and assessments. The tool consists of a set of questions to measure four positive emotions (enjoyment, pride, hope and relief) and five negative emotions (anger, anxiety, hopelessness, shame and boredom). The questions of the questionnaire tool are categorized based on six different sections in online learning: online access, online familiarization reading activities, learning through online community, online assessments, and lesson break activities

C. *Measuring the online learners' level of learning*

The research study proposes six different parameters to measure the learning level of the online learner and it will be evaluated at the end of the learning process [11]. The research study suggests that the final grades of the learners and marks will not only demonstrate the learning performances but also some other parameters learner performances. These parameters are observable measurements which trace or measure learner performances without disturbing the learner's physical behavior [11]. The six parameters are as follows;

X_1 : Average deviation from the expected time spent on each learning activity

X_2 : Average deviation from the expected time spent on each lesson break activity

X_3 : Deviation from the expected time spent on chat

X_4 : Deviation from the expected time spent on browsing and navigation in the LMS

X_5 : Average continuous assessment marks

X_6 : Average discussion forum marks

Therefore, the research has made a hypothesis as "Level of Learning is a function of above mentioned parameters." The hypothesis shall be tested using an experiment conducted on measuring the level of learning in an online learning environment [11]. Suppose Y_i is the level of learning of a student, then

$$Y_i = f(X_1, X_2, X_3, X_4, X_5, X_6)$$

VI. Results and outcomes of Affective E-learning Model

The very first step of the data analysis is to check whether the observed data set is normally distributed. Examining residuals is a key part of all statistical modelling, including design of experiment since the data are plotted against a theoretical normal distribution in such a way that the points should form an approximate straight line.

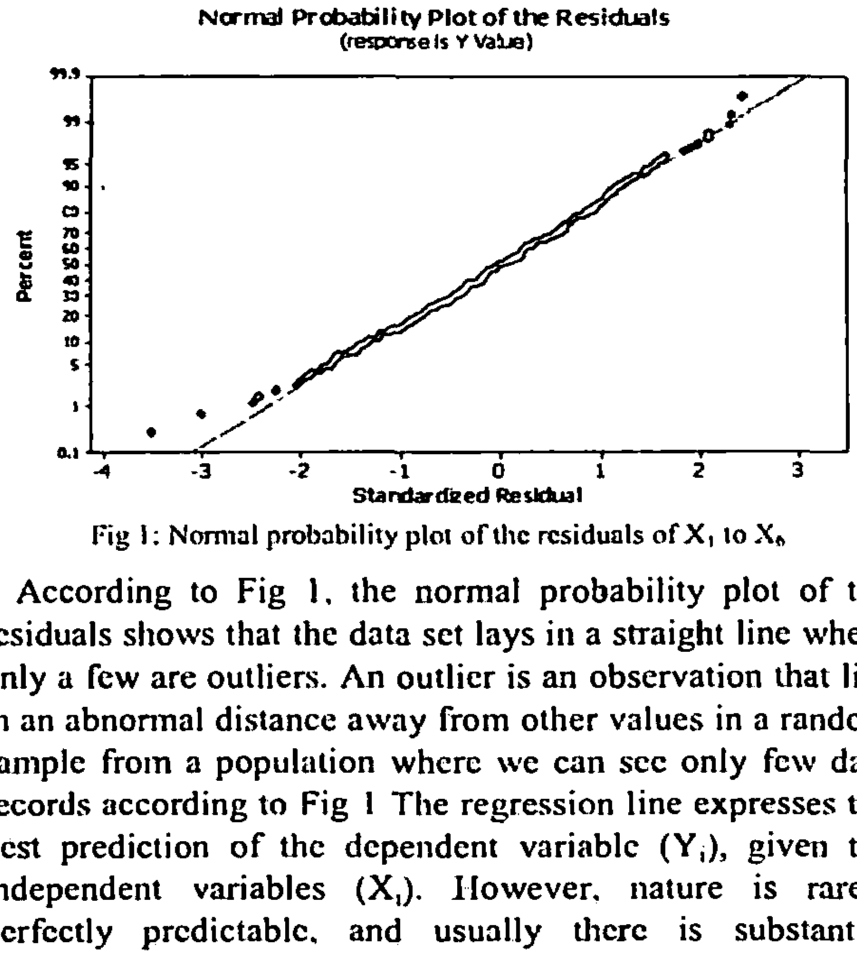


Fig 1: Normal probability plot of the residuals of X_1 to X_6

According to Fig 1, the normal probability plot of the residuals shows that the data set lays in a straight line where only a few are outliers. An outlier is an observation that lies in an abnormal distance away from other values in a random sample from a population where we can see only few data records according to Fig 1 The regression line expresses the best prediction of the dependent variable (Y_i), given the independent variables (X_i). However, nature is rarely perfectly predictable, and usually there is substantial variation of the observed points around the fitted regression line.

A. Multiple regression analysis to derive the model of level of learning

Since the research study of measuring the online learners' level of learning focusing on analysing the relationship between the above mentioned parameters and the learner's actual learning level, the statistical model will be the application of "Multiple Regression Analysis". In our model there are six independent variables namely X_1, X_2, X_3, X_4, X_5 and X_6 and one dependent variable namely Yi. Multiple linear regression approach has the relationship between a scalar dependent variable Y_i and more independent variables. The statistical model for multiple linear regression is;

$$Y_i = a_0 + a_1X_{1i} + a_2X_{2i} + a_3X_{3i} + a_4X_{4i} + a_5X_{5i} + a_6X_{6i} + e_i$$

Accordingly, in the regression model,

Y_i = Learning level of the online learner

X_1, X_2, X_6 = Identified observable parameters

a_0=Intercept,a_1:a_6 : Slope coefficients for X_1 X_6

e_i = Error term for i^{th} observation

According to the correlation analysis following relationships was established. There X_2 / X_4, X_1 / X_5 and X_5 /X_6 shows positive relationships where correlation coefficients are greater than 0.5 and X_2 /X_3, X_3 / X_5 shows negative relationships. Therefore according to the statistical data analysis of multiple regression model with the standard errors is shown below.

$$Y = 2.15\ (0.3965) + 0.0123\ (0.01647)\ X_1 - 0.0059\ (0.02958)\ X_2 - 0.0199\ (0.005982)\ X_3 + 0.00369\ (0.008734)\ X_4 + 0.574\ (0.03895)\ X_5 + 0.0976\ (0.04390)\ X_6$$

The next step is to check the correlation coefficients and the p-values of the independent variables. According to the p-values of independent variables of X_1, X_2 and X_4 have p-values higher than 0.05 and those variables can be rejected from the equation since there is no direct relationship. The p-values of X_3, X_5 and X_6 are equal to 0.001, 0.000 and 0.027 respectively. Since the p-values of X_3, X_5 and X_6 are less than 0.05 at 95% confident level the model can be reproduced and the new model is;

$$Y = 2.15 - 0.0199\ X_3 + 0.574\ X_5 + 0.0976\ X_6$$

Where Y = Learning level of the learner

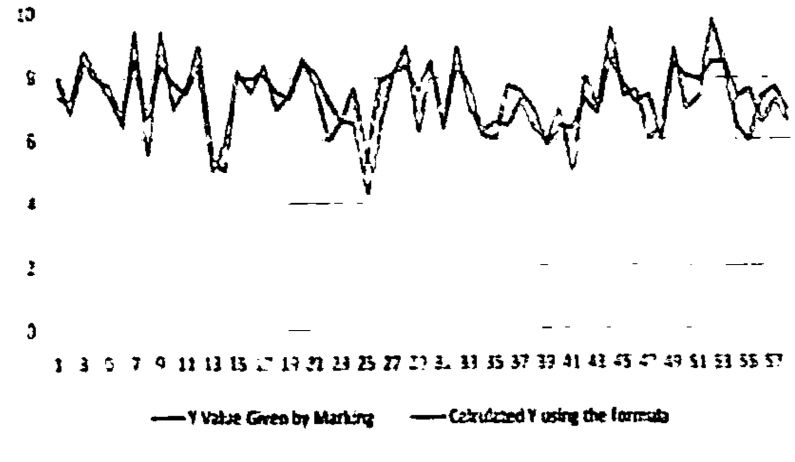
X_3: Deviation from the expected time spent on chat

X_5: Average continuous assessment marks

X_6: Average discussion forum marks

R-Squared used to interpret how better one term is predicting another. According to the model the R-Sq (R^2) has shown as 66.7%.

The statistical analysis of measuring the online learners' level of learning gives that the learning level of online learners can be measured using above three parameters. Therefore the predictors X_1, X_2 and X_4 are being removed from the new regression model. As per given above the rejected independent variable X_1 has a positive relationship with X_5 where the Correlation Coefficient is 0.331. Also the rejected predictor X_2 has a negative relationship with X_3 having Correlation Coefficient of 0.15. The rejected variable X_4 has no direct relationship between X_3, X_5 and X6 but the X_4 shows a positive relationship with X_2. Therefore the relationship of rejected predictors with the level of learning connected via accepted predictors is listed out in the new regression model.



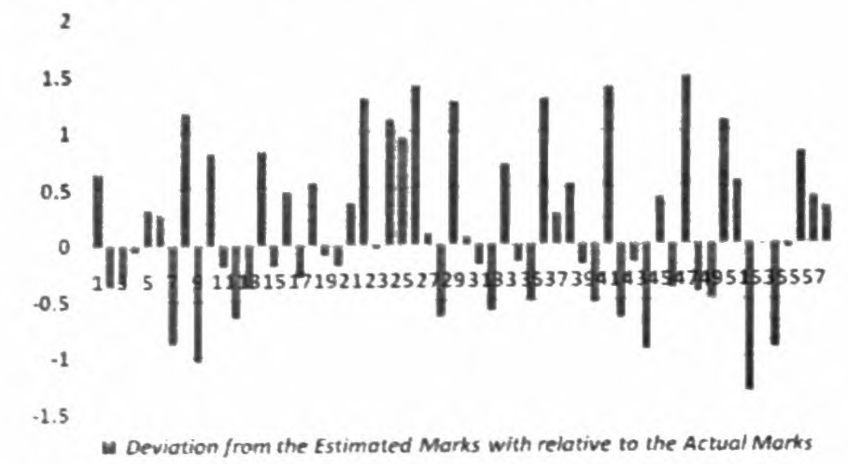


Fig 2: Distribution of estimated Y values obtained through the model equation vs. the actual Y value obtained

It is vital for a test to be valid in order for the results to be accurately applied and interpreted. Testing for validity of the regression model was planned to conduct using the adult learners who are following the degree programmes. The average age group of the learners is in between 18-23. The research has selected to conduct the reliability and validity test for 58 online learners who are following different degree or professional programmes.

The data has been collected pertaining to the parameters X_3, X_5 and X_6 and are applied to the model equation. Also the study has collected the Y_i values separately to see the differences in-between the estimated Y_i value obtained through the model equation. Fig 2 shows the distribution of actual estimated Y_i value through the model equation vs. the actual Y_i value obtained through the experimental analysis. According to Fig 2, it is observable that the data has nearly an equal pattern. The total deviation also varies in between -1.313 to +1.47. The results of the validation set show that the average value of deviation is equal to 0.136 which is less than 1. According to the relative error calculation statistics it has shown that the relative error is equal to 3.028%. The research shows that that there is a very less percentage of the relative error in the regression model which measures the level of learning.

B Measuring the online learners' emotions

The emotion measurement has been monitored during the online learning process. The study has used the online AEQ to assess course-specific and state achievement emotions and the instructions were given during the learning process in the prepared LMS and learners were to state the general, typical emotional experiences when attending class. Altogether there were 244 learners who submitted the online AEQ correctly during the final user study.

TABLE I. RELIABILITY TEST RESULTS OF ONLINE AEQ

	Enjoyment	*Hope*	*Pride*	*Anger*	*Anxiety*	*Shame*	*Hopelessness*	*Boredom*
Case Processing Summary								
Cases Valid (%)	100	100	100	100	100	100	100	100
Excluded (%)	0	0	0.4	0	0	0	0	0
Reliability Statistics								
Cronbach Alpha	0.7	0.8	0.6	0.8	0.8	0.8	0.8	0.8
No of Items	6	6	6	9	11	11	11	11

The internal consistency or the reliability of online AEQ refers to the consistency of a measure of the tool. A measure is said to have a high reliability if it produces consistent results under consistent conditions. The alpha reliability of the variable is derived by assuming that each item represents a retest of a single item. The table 1 shows the reliability results of the online AEQ. The cronbach alpha greater than 0.7 is desirable for indexes that are used as a scale. According to the statistical analysis, the seven emotions out of eight emotions shows the internal consistency or the reliability since the α value is greater than 0.7. The emotion pride shows the α value less than but closer to 0.7 (i.e. 0.647) which means the tool is not reliable in measuring the learning related pride.

The next analysis out of online AEQ is to evaluate the probability plot of the measured data. The normal probability plot provides a graphical representation of data set for assessing whether or not a data set is normally distributed. The data are plotted against a theoretical normal distribution in such a way that the points should form an approximate straight line. The following Fig 3 shows the probability plot of the measured emotions. The graph clearly shows that the data has been categorically divided into two sections which show the clear distinction between positive and negative emotions. Further the graphical evaluation shows that the data set has normally distributed. The overall mean values of the positive emotions vary from 3.86 to 4.05 where the average mean value of three positive emotions as 3.942. Also the study shows the overall mean values vary in-between 2.33 to 2.73 where the average mean value is equal to 2.466

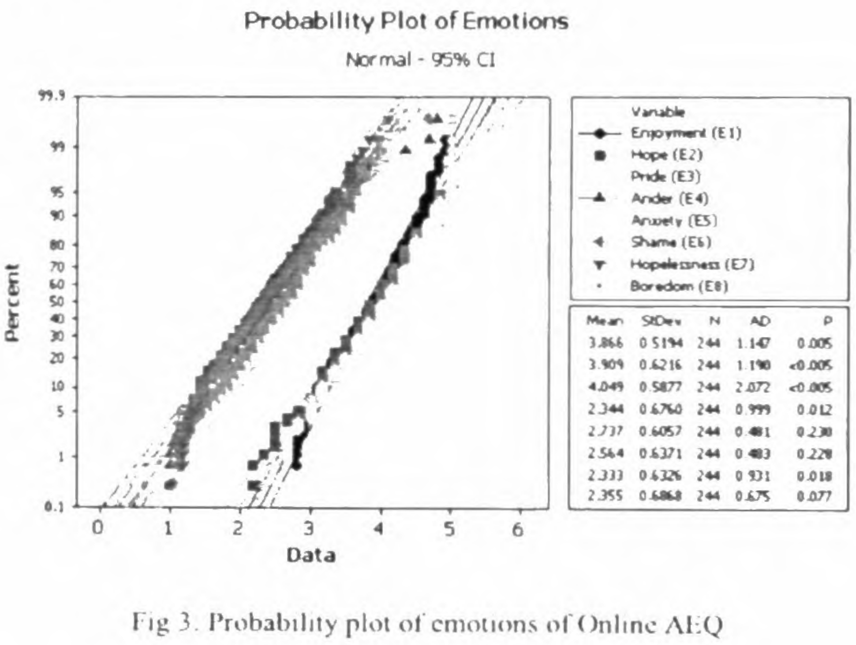


Fig 3. Probability plot of emotions of Online AEQ

C. Co-relation of learner emotions and measured parameters

The next observation of the data analysis is given in between the measured emotions through online AEQ and the parameters used to measure level of learning of an online learner. The rationale behind finding the co-relationship in between those two measures is to hypothetically tested on the relationship between learner behaviour and emotions. According to Fig 3 shows the correlation coefficients in between each eight emotions and the six parameters used to measure the level of learning of an online learner. As per the correlation table all the parameters do not shows a significant correlation with the measured emotions. There are few measurements which exist without showing a significant correlation.

The graph indicates that there is a significant relationship between the emotions and measured behaviour of the online learners. The very first measured predictor was X_1 and it had been measuring the average deviation of expected time spent on each learning activity. There the graph indicates that there are significant positive relationships and negative relationships established. The second parameter X_2 measured the average deviation time spent on lesson break activities. There the graph clearly shows that there is a significant positive relationship between the positive emotions, which is 'enjoyment' and a negative relationship between 'anxiety', 'shame' and 'hopelessness'. The results again indicate that the examined relationship was significant and moderate. The next predictor has shown a good relationship between the emotions. The X_3 predictor measured the learners deviation from the expected time spent on chat forum. As per the results the learners have enjoyed participating in the chat forum since there is a significant strong positive relationship between X_3 and emotions 'enjoyment' and 'hope'. Also the moderate negative relationship between 'shame' and X_3 can be observed.

The measurement or the predictor X_4 was to observe the deviation from the expected time spent on browsing and navigation in the LMS and the graph clearly show that there is absolutely no significant relationship between any positive or negative emotions. The next observations are on the relationship between predictor X_5 which measures the average continuous assessment marks (quiz mark) of the online learners.

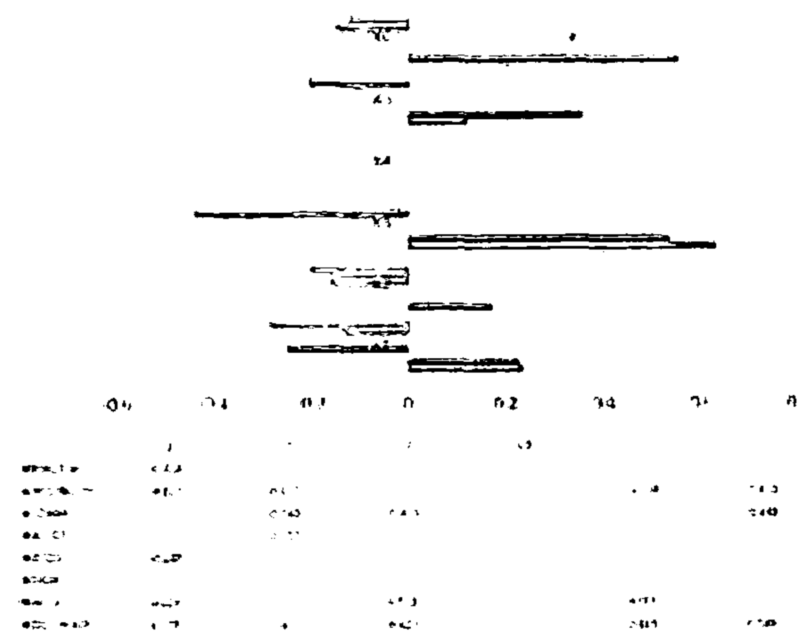


Fig 4: The relationship between the emotions and measured parameters of level of learning

It is observable in Fig 4 that there is a clear significant positive relation in between the positive emotions 'enjoyment' and 'hope'. The last predictor X_6, measured the average discussion forum marks and it can be observed that there is a significant positive relationship between 'enjoyment' and low negative relationships between emotions 'shame' and 'hopelessness'.

D. Relationship between Learning Activities Under X_1 and Emotions

As per the graph the study predicts on the behaviour of each emotion corresponding with the each behaviour measurement. In considering the first parameter X_1 which is the average deviation time spent on each learning activity, the study can further can elaborate the relationship with each emotion using Fig 5. There were sub activities covered under the learning experiences such as following the reading activity, self-assess quiz, discussion forum, assignment and mind map. The time related measurements were based in calculating the average deviation of expected time spent on each learning activity mentioned above. There the study has further examined the relationship between the learning activities mentioned above with the emotions measured using online AEQ. The Fig 5 shows that both negative and positive emotions showed a significant relationship among the activities. These relationships were established as linear relationships which are significantly related. This may be the reason behind observing multiple positive and negative emotions in the relationship graph shown in Fig 5 under the predictor X_1.

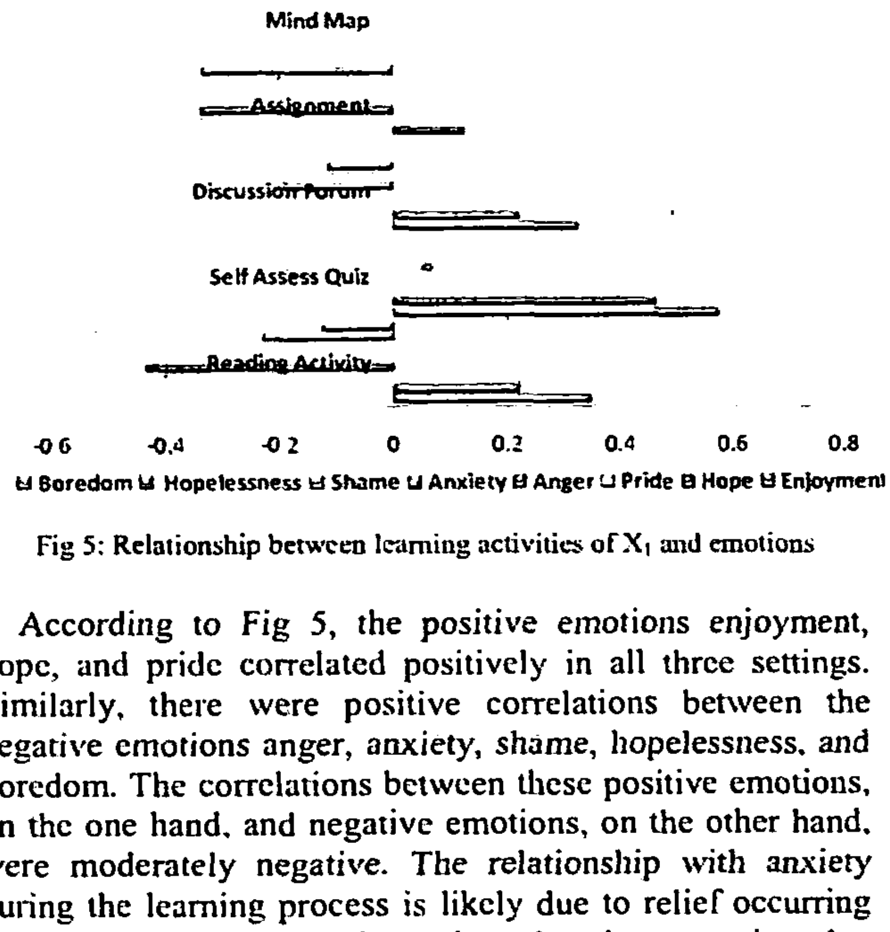


Fig 5: Relationship between learning activities of X_1 and emotions

According to Fig 5, the positive emotions enjoyment, hope, and pride correlated positively in all three settings. Similarly, there were positive correlations between the negative emotions anger, anxiety, shame, hopelessness, and boredom. The correlations between these positive emotions, on the one hand, and negative emotions, on the other hand, were moderately negative. The relationship with anxiety during the learning process is likely due to relief occurring when anxiety-inducing threat is reduced, suggesting that relief is often preceded by anxiety during online learning activities.

VII. CONCLUSIONS

This research study has focused on the problem of not recognising e-learners emotions during learning experience. The study has defined the aim of the research as to "develop a computational model to recognise students' emotions in online learning systems". Therefore the study has developed the novel approach of affective e-learning model and which was described in the high level architecture. The study adopted an experimental based approach in measuring, testing and validating the current e-learning system. Finally, this exploratory research and empirical study has developed the affective e-learning model based on Barry Kort's affective learning model. This model is described by two major constructs which are the learning level of individual learner and the emotional state of the learner. Affect recognising and finding the exact quadrant has to be done together by measuring the learning level of the learners. The research study identified six different parameters to measure the learning level of the online learner and they are evaluated at the end of the learning process. The emotional element of the leaner is measured using multidimensional self-reported instrument which assesses online learner's individual emotional reactions in achievement situations. The tool is termed as Achievement Emotion Questionnaire for Online Learning and four positive emotions and five negative emotions are measured in the real time online learning environment. The learner's emotional state and the level of learning is mapped in two dimensional space and the responses are used to enhance leaner performances.

The study is checked for the consistency or the reliability of online AEQ and it has been proves that the Online AEQ is a reliable measure which can be used to measure the online learners emotions in achievement situations. According to the statistical analysis of the AEQ the study proves that there is a significant relationship between the emotions and measured behaviour of the online learners. Further the results of the research study has elaborated that there were significant relationship between the emotions obtained through AEQ and the independent variables use to measure the level of learning of online learners. Further the results indicated that there is a significant relationship between the emotions and independent variables measured. There was a significant correlation between the positive emotions such as 'enjoyment', 'pride', 'hope' with the positive responses of the facilitators as well as pleasurable activities such as chat forums and lesson break activities. The novel approach of affective e-learning model open up the new directions in affective computing and e-learning.

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