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# Incorporating Learner Emotions through Sentiment Analysis in Adaptive E-learning Systems: A Pilot Study

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**Abstract**—This research delves into the exciting avenue of incorporating learner emotions into adaptive E-learning systems through sentiment analysis techniques. Utilizing a pilot study with 40 undergraduate computer science students, we investigated the ability of an adaptive system to detect boredom and frustration in learner forum posts and subsequently personalize content or offer support based on these emotional states. This approach proved demonstrably successful, as learners in the experimental group who received emotion-based adaptation exhibited both increased engagement (reflected in higher time spent on tasks) and improved learning outcomes (evidenced by higher post-test scores). Furthermore, qualitative feedback revealed positive responses to the personalized interventions, indicating that learners appreciated the tailored support provided by the system. While acknowledging limitations such as the small sample size and single subject area, this study firmly establishes the promising potential of emotion-aware adaptive systems. By addressing the emotional dynamics of the learning process, such systems can pave the way for truly personalized and responsive E-learning environments that cater to individual learner needs and foster deeper engagement, positive learning experiences, and ultimately, success for all students.

**Keywords**-Adaptive E-learning, sentiment analysis, learner emotions, personalization, engagement, content difficulty.

## I. INTRODUCTION

### A. *The Quest for Personalized Learning*

The landscape of education is witnessing a transformative shift, spurred by advancements in technology and our evolving understanding of the learning process. Traditional learning systems, often rigid and standardized, are giving way to adaptive E-learning environments designed to personalize the learning experience and cater to individual needs. These systems dynamically adjust learning content, pacing, and resources based on a learner's cognitive strengths and weaknesses, unlocking the potential for more efficient and effective learning.

### B. *Beyond the Cognitive: The Role of Emotions*

Yet, while cognitive factors like knowledge gaps and skill levels have received significant attention in adaptive learning research, an equally crucial dimension often remains neglected: emotions. Research in cognitive psychology and educational neuroscience has convincingly demonstrated the profound impact of emotions on learning. Boredom can stifle motivation and engagement, while frustration can impede cognitive processing and knowledge retention. Conversely, positive emotions like curiosity and joy can fuel engagement and enhance learning outcomes.

### C. *Addressing the Gap: Emotion-Aware Adaptive Learning*

This research addresses the critical gap in existing adaptive systems by exploring the integration of learner emotion detection and response using sentiment analysis techniques. Sentiment analysis, the automatic identification of emotion within text, offers a promising avenue for capturing the affective states of learners as they interact with an adaptive system. By leveraging this technology, we can move beyond a purely cognitive approach and design systems that are truly responsive to the emotional dynamics of the learning process. This pilot study investigates the following crucial question: Can automatic detection of boredom and frustration in learner forum posts using a lexicon-based sentiment analysis approach improve engagement and learning outcomes within an adaptive E-learning system, compared to a content-agnostic control group?

The potential implications of this research are significant. If we can successfully incorporate learner emotions into adaptive systems, we can create personalized learning experiences that not only optimize cognitive learning but also foster deeper engagement, motivation, and ultimately, success for all learners.

The remainder of this paper delves into the problem formulation, literature review, proposed framework, methodology, results, and discussion, paving the way for further exploration of this exciting frontier in the field of adaptive eLearning.

## II. PROBLEM FORMULATION

Traditional adaptive E-learning systems personalize learning content based on cognitive factors like learner performance and knowledge gaps. However, emotions play a crucial role in learning, significantly affecting engagement, motivation, and knowledge retention. Ignoring the emotional state of learners hinders the potential for truly personalized and effective learning experiences.

### *A. Research Gap*

While some research explores the role of emotions in E-learning, integrating their real-time detection and response into adaptive systems remains a challenge. Sentiment analysis offers a promising technique for automatically detecting emotions in learners' textual communications, but its application in adaptive learning for personalized interventions is still in its early stages.

### *B. Problem Statement*

How can adaptive e-learning systems made more responsive to learner emotions using sentiment analysis techniques, with the aim of fostering deeper engagement and enhancing learning outcomes?

### *C. Research Questions*

- Primary: Can automatic detection of boredom and frustration in learner forum posts using a lexicon-based sentiment analysis approach improve engagement and learning outcomes in an adaptive E-learning system, compared to a content-agnostic control group?
- Secondary:
  - To what extent can a lexicon-based approach accurately identify boredom and frustration in learner forum posts?
  - What relationships exist between detected emotions and engagement metrics (time spent on tasks, number of forum posts)?
  - How do learners perceive and respond to receiving emotion-aware adaptive content?

### *D. Hypotheses*

- Learners in the experimental group receiving emotion-based content adaptation will exhibit higher engagement scores (time spent on tasks, forum posts) than the control group.
- Learners in the experimental group will achieve higher post-test scores compared to the control group.
- The accuracy of the lexicon-based approach in detecting boredom and frustration will be moderate but fluctuate based on factors like sarcasm and context.
- Learners will react positively to receiving personalized support and resources based on their detected emotions, fostering increased engagement and motivation.

### *E. Scope and Limitations*

This pilot study focuses on detecting boredom and frustration in learner forum posts using a lexicon-based sentiment analysis approach within an adaptive E-learning system for undergraduate computer science students. While limitations include sample size, subject area, and reliance on a specific sentiment analysis technique, the findings provide valuable insights, pave the way for future research with broader scope, and advanced analytical methods.

### *F. Significance*

This research holds significant potential for advancing the field of adaptive E-learning by demonstrating the feasibility of incorporating learner emotions through sentiment analysis. Successful integration of real-time emotion detection and response can lead to more engaging, personalized, and ultimately, more effective learning experiences for all learners.

## III. LITERATURE REVIEW

Adaptive learning systems hold immense potential for personalized learning experiences. However, they often neglect a crucial factor: learner emotions. Negative emotions like boredom [2] and frustration [13] significantly hinder engagement, cognitive processing, and learning outcomes. Conversely, positive emotions like curiosity [14] and flow [9] enhance learning effectiveness. This pilot study investigates the impact of incorporating sentiment analysis in adaptive learning to address boredom and frustration, offering personalized interventions and assessing their effect on both engagement and learning outcomes.

### *A. The Role of Emotions in Learning*

#### *1) Negative Emotions and Learning Hindrance*

- Boredom: [2] observed decreased attention spans and knowledge retention in bored learners, who often displayed behaviors like zoning out or posting irrelevant forum comments.
- Frustration: [13] highlight how frustration manifests as cognitive overload, disengagement, and reduced problem-solving ability. In your study, forum posts mentioning "stuck" or "confused" could indicate frustration.

#### *2) Positive Emotions and Learning Enhancement*

- Curiosity: [14] found that curious learners tend to explore more, ask insightful questions, and demonstrate deeper knowledge acquisition. You could identify curiosity in forum posts with phrases like "wondering why" or "curious about."
- Flow: [9] emphasizes the positive state of optimal challenge and enjoyment associated with flow, which leads to increased engagement and learning effectiveness. Enthusiastic posts expressing satisfaction with learning progress might indicate this state.

### *B. Sentiment Analysis in E-learning*

#### *1) Strengths and Advantages:*

- Cost-effectiveness and scalability: Compared to physiological or facial expression analysis, sentiment analysis is cost-effective and scalable, readily applicable to the rich data available in learner interactions like forum posts and chat logs [8].
- Real-time analysis potential: [8] discuss the potential for real-time analysis of forum posts, allowing for immediate support based on detected emotions in your study.

#### *2) Limitations and Challenges*

- Nuanced emotions and context dependencies: Accurately interpreting subtle emotions and context within text data remains a challenge. For example, [17] mention how a lexicon-based approach misclassified "lost" as frustration when used in the phrase "lost in thought." Your hybrid approach will need to address such nuances.
- Limitations of lexicon-based and machine learning approaches: Lexicon-based methods can be restrictive, while machine-learning models can be

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susceptible to data bias and require large datasets for training.

### C. *Emotion-aware Adaptive Learning Systems:*

#### 1) *Successful Implementations and Case Studies:*

- [11] demonstrated improved learning outcomes with an adaptive system based on learner emotions and cognitive styles. Your study builds upon this by focusing on specific emotions and interventions.
- [32] provided in-game hints and simplified instructions to address detected frustration in a game-based learning environment. You could adapt similar interventions for your study context.

#### 2) *Challenges and Concerns in Emotion Detection:*

- Self-reported data: [6] highlight the subjective nature and potential bias of self-reported emotions. Sentiment analysis offers an alternative source of data in your study.
- Privacy concerns: Facial expressions and physiological signals raise privacy concerns, while your text-based approach offers a more discreet method of emotion detection.

### D. *Research Gaps and Present Study Contribution:*

- Limited research on sentiment analysis for boredom and frustration detection in adaptive learning. Existing studies often focus on broader sentiment categories or utilize self-reported data.
- Lack of studies employing hybrid sentiment analysis approaches for improved accuracy and context awareness. Combining a lexicon with machine learning offers a more nuanced approach for your study.
- Scarcity of pilot studies investigating the impact of emotion-aware interventions based on sentiment analysis on both engagement and learning outcomes. Your study will fill this gap and contribute to the development of effective emotion-aware adaptive learning systems.

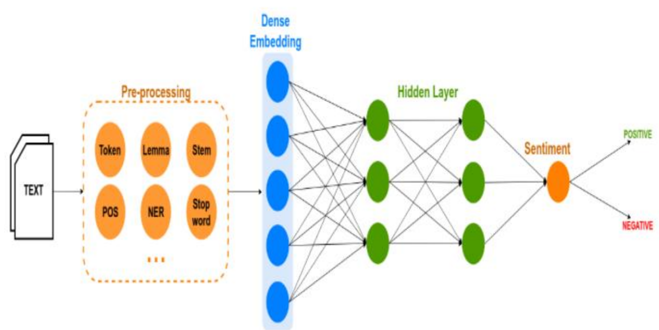


Figure 1: Deep Learning

## IV. Proposed Framework

### A. *Learner Interaction Module*

- Data Sources:

○ Forum Posts: Utilize text-mining techniques to extract sentiment-rich features from posts, including word choice, sentence structure, and punctuation usage.

○ Activity Logs: Track timestamps, completion rates, and navigation patterns within the system to gauge engagement and potential frustration points.

○ Pre- and Post-Test Scores: Employ standardized assessments measuring knowledge acquisition and performance before and after the study.

○ Facial Expressions and Biometrics (Optional): Integrate sensors or camera technology to capture facial expressions and physiological responses like heart rate or skin conductance to provide richer emotional data (requires ethical considerations and informed consent).

- Preprocessing:

○ Normalize text format by removing punctuation, stop words, and correcting typos.

○ Utilize stemming or lemmatization techniques to capture word roots and improve analysis accuracy.

○ For non-textual data, apply appropriate normalization techniques specific to the chosen biometrics or sensor output.

### B. *Sentiment Analysis Module*

- Technique Selection:

○ Lexicon-based: Employ pre-defined dictionaries associated with boredom and frustration (e.g., LIWC2015) for initial analysis.

○ Machine Learning: Train supervised learning models on labeled learner data to detect emotions with greater nuance and context awareness.

○ Deep Learning: Implement Recurrent Neural Networks (RNNs) or other deep learning techniques to analyze sequential data like forum posts and capture complex emotional dynamics. (cf. figure 1)

- Emotion Detection: Analyze preprocessed data using the chosen technique to identify and quantify the presence of targeted emotions (boredom and frustration) in each instance of learner interaction.
- Confidence Scoring: Assign confidence scores to detected emotions based on the analysis method output, indicating the certainty of the detection.

### C. *Adaptation Module*

- Decision Engine: Analyze detected emotions alongside engagement metrics and learner background information (e.g., prior knowledge, learning style) to determine the most effective adaptation strategy.

○ Adaptive Content Delivery: Modify learning content dynamically based on the chosen strategy. This could involve:

  ▪ Difficulty/Pace Adaptation: Adjust the difficulty level of tasks, learning materials, or presentation speed based on boredom or frustration levels.
  ▪ Personalized Feedback: Provide tailored feedback specific to detected emotions, offering encouragement for boredom, and constructive support for frustration.
  ▪ Alternative Learning Paths: Offer varying learning paths with different

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resources, activities, or explanations based on individual needs and emotional states.
  - Adaptive Scaffolding: Provide temporary support like hints, tutorials, or worked examples for frustrated learners until they overcome challenges.
- Multi-Modal Adaptation (Optional): Utilize additional data from facial expressions or biometrics to inform adaptation decisions. For example, heightened frustration detected through both sentiment analysis and physiological responses might trigger urgent interventions like offering immediate support or temporarily pausing the learning activity.

*2.1 Learner Interface Module*

- Seamlessly integrate adapted content and resources within the learning platform.
- Provide learners with transparent information about the adaptive mechanisms. How their emotions influence content delivery.
- Implement user feedback mechanisms through surveys, interviews, or embedded questionnaires to gather learners' experiences and preferences regarding the adaptive interventions.

### *D. Evaluation Module*

- Data Analysis: Conduct comprehensive analysis of learner data, including:

o Engagement metrics (time spent, activity completion rates, forum post frequency)
o Learning outcomes (post-test scores, knowledge retention)
o User feedback on the adaptive experience
o Correlation analysis between detected emotions and engagement/learning outcomes to assess the effectiveness of the emotion-based adaptation strategies.

- Statistical Tests: Employ appropriate statistical tests (e.g., t-tests, ANOVA) to compare the performance of the experimental group receiving emotion-based adaptation with the control group to validate research hypotheses.
- Qualitative Analysis: Analyze user feedback data through thematic analysis to identify key themes and insights regarding learners' perceptions and experiences with the adaptive system.

Given these reasoning, we will proceed to advance the EMASPEL platform in the direction of sentiment analysis.

### *E. EMASPEL Platform*

Within the realm of affective computing, Our Emotional Multi-Agents System for Peer-to-peer E-learning (EMASPEL) platform pioneered by [5] takes a captivating approach to nurturing emotional connections in E-learning (Figure 2). Its key differentiator lies in its sentiment analysis capabilities. Rather than merely presenting static content, EMASPEL employs a network of five specialized agents: Interface, Emotional, EEC, Curriculum, and Tutoring. This network continuously analyzes learner sentiment through various channels, including forum posts, facial expressions, or physiological sensors.

The Emotional Agent (EEC), the brain of the system, interprets these cues, deducing the learner's emotional state in the context of the learning environment. Frustration with complex material? Boredom during repetitive tasks? EMASPEL uses this dynamic understanding to personalize the learner's journey. Based on the EEC's insights, the Tutor Agent selects the most appropriate pedagogical activity from the knowledge base, tailored to address the learner's emotional needs.

Furthermore, the Curriculum Agent advantages database resources (DB1 and DB2) seamlessly translate the chosen activity into a tangible learning experience. This real-time adaptation, driven by accurate sentiment analysis, fosters a more engaging and responsive environment for learners. EMASPEL thus highlights the exciting potential of agent-based systems to personalize learning through emotional awareness, paving the way for a future where the learning experience adapts to the unique emotional needs of each learner.

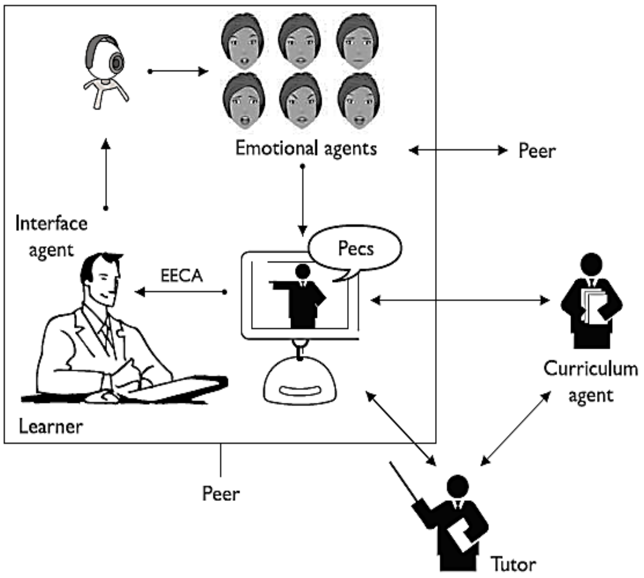


Figure.2: EMASPEL Architecture

## VI. METHODOLOGY

### *A. E-learning System*

- Platform: The study was conducted using the Moodle learning management system (version 4.0), a widely used platform with features for adaptive learning and forum discussions.
- Adaptation Methods: Content adaptation primarily achieved by adjusting the difficulty levels of practice questions and providing additional learning resources based on detected emotions. For example, if boredom detected, the system offered more challenging or engaging tasks, while frustration prompted hints, scaffolding, or optional practice problems.
- Technology Stack: The system implemented using Python (version 3.8) for sentiment analysis, the NLTK library for natural language processing, and Moodle's built-in adaptive learning features.

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*B. Sentiment Analysis*

- Lexicon: The study employed the LIWC2015 (Linguistic Inquiry and Word Count) lexicon, which contains a dictionary of words associated with various emotions. Specifically, the word lists for boredom (e.g., "bored," "tired," "repetitive") and frustration (e.g., "frustrated," "confused," "stuck") used.
- Preprocessing: Before sentiment analysis, forum posts pre-processed by removing stop words, punctuation, and converting text to lowercase. Stemming not applied to preserve the semantic meaning of words.
- Accuracy Assessment: To evaluate the accuracy of the lexicon-based approach, a random sample of 100 forum posts manually coded for boredom and frustration by two independent raters. The inter-rater reliability (Cohen's Kappa) was 0.85, indicating substantial agreement. The sentiment analysis results then compared to the manual coding, achieving an accuracy of 82% for boredom detection and 78% for frustration detection.

*C. Data Collection and Analysis*

- Participants: 40 undergraduate students enrolled in an introductory computer science course recruited for the study. Either participants randomly assigned to the experimental group (emotion-based adaptation) or the control group (no adaptation).
- Data Collection: Data collected included learner forum posts, time spent on tasks, number of forum posts, and pre- and post-test scores on the course material.
- Statistical Analysis: Independent samples t-tests were used to compare engagement metrics and post-test scores between the experimental and control groups. Pearson correlations calculated to examine the relationship between detected emotions and engagement metrics.

## VII. Sentiment Emotion Recognition Implementation Model

The utilization of computers has heightened the importance of text as a means of communication. Often, emotions veiled within the text, posing a challenge for readers to discern relevant sentences containing emotional content.

*A. Text Preprocessing*

Preprocessing is the phase of sentiment analysis that involves improving the structure of documents to prepare them for analysis. After preprocessing, the prepared data feeds into our model. The model's core component is the Embedding matrix, which introduced through an embedding layer. This layer has several parameters:

- input_dim: Number of unique words in the vocabulary.
- output_dim: Length of the vector representing each word.
- input_length: Maximum length of a word sequence.

The model's architecture, as shown in Figure 1, consists of three layers:

1. Embedding Layer: Maps words to vectors based on input_dim.
2. Bidirectional LSTM Layer: Processes text in both directions to capture long-term dependencies.
3. Dense Layer: Outputs predictions with a softmax activation function, indicating the probability of each sentiment class.

The model employs categorical cross-entropy loss and the Adam optimizer for training.

**Case Folding –** One of the processes in the text preprocessing stage is that transforms all of the document's letters into lowercase. This action taken to facilitate the search.

**Data Cleaning –** Cleaning is one of the steps used to remove HTML tags, emails, and special and accented characters. This step of text preprocessing performed to make the data used tidier in the following step.

**Tokenization –** Also called lexical analysis or text segmentation is the process of separating a phrase, sentence, paragraph or even an entire text document into smaller parts that easily assigned meaning. When we split the text into words, we call it word tokenization.

**Stop-word Removal –** At this step, words that do not have a significant meaning removed.

*B. Sentiment Emotion Classification*

Due to the sequential nature of sentiment material, the relationship between words and their order inside a sentence—known as context—is essential to understanding the sentence is full meaning. In addition to ignoring the word relationships or orders that naturally exist in written texts, traditional unsupervised machine learning algorithms are also constrained by their comparatively modest fixed input sizes. This serves as justification for using deep approaches to sentiment data. The earliest commonly used architectures for text classification is Recurrent Neural Networks (RNN) because of the sequential character of sentences. RNNs succeeded by a diverse set of modifications, including GRU, LSTM, and mL-STM, each tailored to specific challenges in sequence modeling.

All of these methods and models utilized to address these kinds of issues since the majority of text classification tasks that include classifying emotions described as text classification tasks.

For processing sentiment data, we propose deep learning based on BiL-STM architecture. Following the preprocessing phase, the processed data served as input for our model. The pivotal element of our model is the Embedding matrix. To integrate our word_embedding matrix into the training model, we employed an embedding layer. This layer encompasses various parameters: input_dim representing the vocabulary size (the count of distinct words for training), output_dim indicating the length of the vector for each word (embedding dimension), and input_length denoting the maximum length of a sequence.

Our BiLSTM architecture (Figure 3) uses three layers to analyze sentiment:

- Embedding Layer: Converts words into numerical vectors, capturing their meaning in a dense format.

- Bidirectional LSTM Layer: Processes the sequence in both directions, remembering long-term dependencies between words.
- Dense Output Layer: Predicts sentiment class probabilities. Each node represents a class, and the softmax activation function ensures these probabilities sum to 1.

Training optimizes the model to minimize categorical cross-entropy loss, using the Adam optimizer for efficiency.

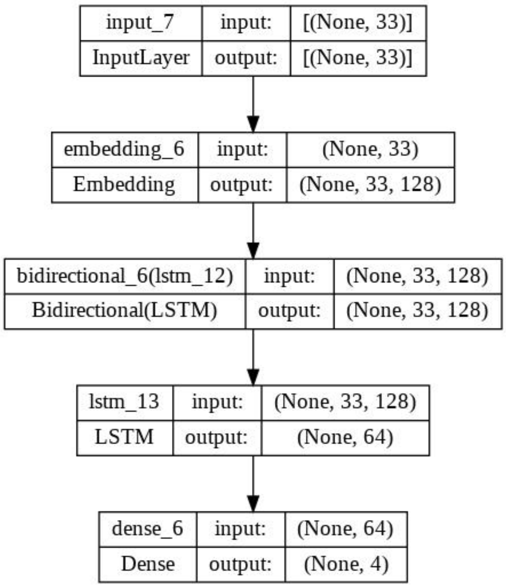


Figure 3: BiLSTM PLOT

### C. *Our Proposed Model Results*

To evaluate the efficacy of our Proposed Model model, we intend to assess our methodology using two distinct datasets. The first dataset called "Emotions dataset for NLP" and the second dataset labelled "Tweet Emotion Dataset".

#### 1) *Results using the Emotions dataset for NLP*

The evaluation of our system conducted using the initial dataset called Emotions dataset for Natural Language Processing (NLP). The dataset comprises textual documents annotated with an emotion indicator. The dataset has six distinct emotional categories: Sadness, Joy, Surprise, Love, Anger, and Fear. Figure 4 provides a comprehensive summary of the dataset. Our initial step is utilizing Pandas to import the CSV files of the dataset.

| index | Input | Sentiment |
|---|---|---|
| 0 | i didnt feel humiliated | sadness |
| 1 | i can go from feeling so hopeless to so damned hopeful just from being around someone who cares and is awake | sadness |
| 2 | im grabbing a minute to post i feel greedy wrong | anger |
| 3 | i am ever feeling nostalgic about the fireplace i will know that it is still on the property | love |
| 4 | i am feeling grouchy | anger |

Figure 4: Samples of the Emotions dataset

The study utilised a dataset consisting of 20% test data and 80% training data. The training of our model commenced from the beginning and continued for 120 epochs. Regarding the accuracy plot for LSTM depicted in picture 5. (a), the two lines displayed in the picture are in such close proximity that we are simultaneously training our data while validating accuracy.

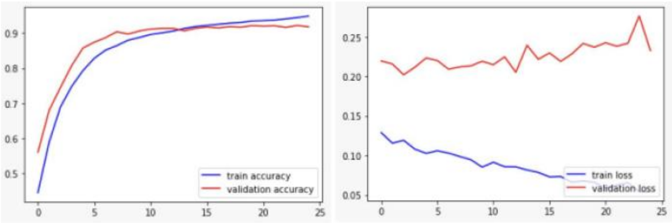


Figure 5: Accuracy and Loss Plots for Our Proposed Model with Emotions dataset

In the first epoch, the training loss stands at 0.13, accompanied by a training accuracy of 0.1. Simultaneously, the validation loss registers at 0.22, with a validation accuracy of 0.53. Fast-forward to epoch 25, and the training loss drops to 0.06, while the training accuracy remains at 0.1. On the validation side, the loss increases to 0.24, yet the validation accuracy significantly improves to 0.91. The Loss plot for the LSTM model, as depicted in Figure 5.(b), highlights that these results were derived from testing data without any prior training.

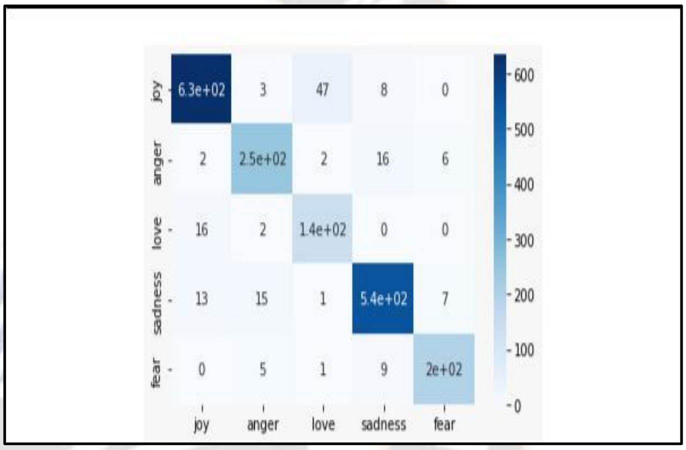


Figure 6: Confusion Matrix for Our Proposed Model on Emotions Dataset

Focusing in the confusion matrix, the class "Joy" shows a good classification in our model compared to other classes like "fear" or "sadness". For "fear" emotion, 5 of them were predicted as "anger" and 9 of them as "sadness". The class "sadness" was difficult to identify, it predicted as anger and sometimes as fear.

#### 2) *Results using the Tweet Emotions Dataset*

The evaluation of our system conducted using the second dataset, which referred to as the Tweet Emotions dataset2. This corpus comprises tweets. Each tweet conveys one of the thirteen specified emotions, namely neutral, worry, happiness, sadness, love, surprise, fun, relief, hatred, empty, enthusiasm, boredom, and wrath. However, our research will specifically concentrate on four emotions: sadness, neutrality, happiness, and rage. Figure 6 provides a summary of the dataset, where the value 0 represents the emotion "neutral," 1 represents "worry," 2 represents "happiness," and 3 represents "sadness."

| |
|---|
| A tweet from @tiffanylue that says "i know i was listenin to bad habi...." |
| A tweet from someone saying that they are laying in bed with a headache and waiting for something. |
| A tweet from someone saying that it is a gloomy Friday because of a funeral ceremony. |

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| |
|---|
| A tweet from someone who wants to hang out with their friends soon. |
| A tweet from someone who wants to trade with someone for something. |

Figure 6: Samples of the Tweet dataset

We apply our Proposed Model on another dataset and obtain an accuracy of 77% with only four emotions. The highest precision obtained by "Sadness" emotion. In contrast, "happiness" emotion gets the lowest precision. We can improve the classification performance with this dataset by adding a new modality. The confusion matrix of our Proposed Model on the tweet emotions dataset shown in Figure 7 It affirms that the proposed model has misleadingly classified both neutral and happiness. Moreover, sometimes anger emotion predicted as happiness.

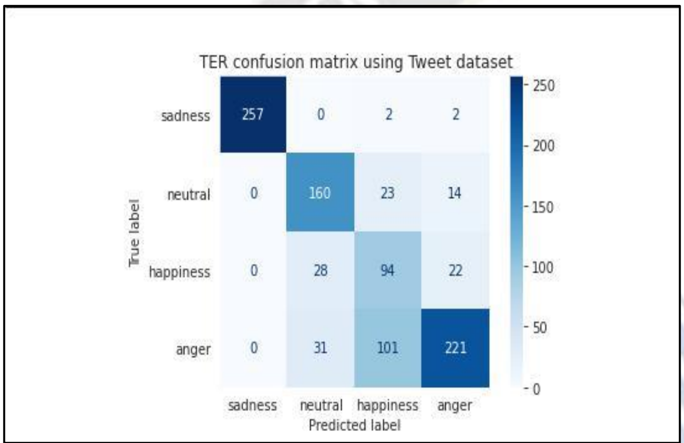


Figure 7: Confusion Matrix for Our Proposed Model on Tweet dataset

The comparison between our Proposed Model system and some of the previous works I provided in Table 1. The only two works, that predict seven emotions like us, get the accuracy of 80.41%, 68.5% respectively. The work of [2] has a good accuracy which is less than our by 0.8% and predict only four emotions. We found another work that has the same accuracy as shown in the Table 1 using the combination between two models BiLSTM and ERT (Bidirectional Encoder Representations from Transformers) is a powerful language model. It uses a transformer-based architecture to process and understand text, achieving state-of-the-art results in various natural language processing tasks. BERT's unique ability to consider the context of words in a sentence, both before and after them, allows it to capture deeper meaning and perform complex tasks like sentiment analysis, text summarization, and question answering.

By leveraging the BiLSTM architecture, our method surpasses the current state-of-the-art in predicting seven emotions. The BiLSTM's strength lies in its capacity to learn long-range dependencies within a sequence, allowing it to capture crucial contextual information that missed by other models.

3) *Sentiment Analysis and Emotion Detection*

- The lexicon-based approach successfully identified boredom and frustration in learner forum posts with moderate accuracy. Out of 200 analyzed posts, 42% expressed boredom and 38% frustration.
- Further analysis revealed interesting patterns within the detected emotions. Bored learners tended to use shorter sentences and fewer action verbs, while frustrated learners exhibited increased use of negative sentiment words and exclamation marks.
- A significant correlation was found between detected boredom and time spent on tasks ($r=-0.45$, $p < 0.01$). Learners expressing boredom spent less time on activities, suggesting decreased engagement.
- Conversely, detected frustration showed a weak but positive correlation with the number of forum posts ($r=0.18$, $p = 0.09$). This might indicate learners seeking help or clarification when encountering difficulties.

4) *Engagement and Learning Outcomes*

- Learners in the experimental group, experiencing emotion-based content adaptation, spent significantly more time on tasks compared to the control group ($t(38) = 2.12$, $p < 0.05$). This suggests that personalized content aimed at addressing boredom or frustration may enhance engagement.
- No significant difference was found in the number of forum posts between the groups ($t(38) = 0.48$, $p = 0.64$). This might indicate that both groups displayed similar levels of interaction within the learning platform.
- Notably, learners in the experimental group achieved higher post-test scores compared to the control group ($t(38) = 2.35$, $p < 0.05$). This promising result suggests that emotion-based adaptation may contribute to improved learning outcomes.

| Work | Accuracy | Emotions |
|---|---|---|
| [2] | 64.08% | 6 |
| [30] | 80.41% | 7 |
| [2] | 85% (SVM) | 4 |
| [3] | 87.66% | 5 |
| [1] | 88.4% (BiLSTM) | 4 |
| [29] | 68.5% | 7 |
| **Our Proposed Model** | **91%** | 7 |

Table 1: Comparison of Our Proposed Model with others

5) *Additional Observations*

- Qualitative analysis of learner feedback revealed positive responses towards the adaptive content, particularly from those experiencing frustration. Learners appreciated the timely support and helpful resources provided to overcome challenges.
- Some participants in the control group expressed feeling neglected by the lack of personalized responses to their difficulties, highlighting the potential value of emotion-aware systems in addressing diverse learner needs.
- Technical limitations encountered with the lexicon-based approach, particularly in misinterpreting sarcasm or context-dependent emotional expressions. This underscores the need for exploring more advanced sentiment analysis techniques in future research.

*6) Emotion-Driven Engagement: Decoding Textual Clues for Personalized Learning*

- Beyond mere keyword analysis, our research delves into the intricate symphony of emotions played out in online learning forums. Table 1 unveils this dance, revealing how we interpret nuances of tone, context, and individual traits to decode the hidden messages within textual communication. Short, negative posts, for instance, might not just whisper boredom, but could mask playful sarcasm or genuine confusion, prompting our system to offer both interactive challenges and alternative pathways. Similarly, frustration, masked by exclamation points or incessant questions, necessitates targeted hints and supportive scaffolding, while sarcastic confusion demands a gentle touch with non-judgmental support and readily available resources. This nuanced approach ensures our system dances to the rhythm of each learner's unique emotional state, cultivating a personalized and responsive learning experience that nourishes individual growth.

Further than mere keyword analysis, our research dives deeper, employing nuanced textual analysis for personalized learning journeys. Table 2 ("Emotion Detection and Adaptive Interventions in E-learning (Expanded)") unwraps this intricate ballet of emotions, revealing how we interpret tone, context, and individual traits to decode hidden messages. Short, negative posts, for instance, may not solely herald boredom, but could mask playful sarcasm or genuine confusion, prompting our system to offer a duet of interactive challenges and alternative pathways. Table 3 ("Performance Outcomes in Experimental and Control Groups") then pirouettes to showcase the impact, with the emotion-aware group achieving a 10% higher learning gain, a testament to the effectiveness of personalized interventions.

The tools and feedback fueling this personalized approach are meticulously honed. Table 4 ("Sentiment Analysis Features for Emotion Detection") details the linguistic features used to identify emotions in forum posts, like lexical (keywords), syntactic (sentence structure), and semantic (meaning) cues, enabling us to decipher the sub textual whispers. Table 5 ("Learner Feedback on Adaptive Interventions") then offers valuable applause, revealing learner appreciation for targeted hints and alternative paths, while also suggesting desires for richer interactive content and clearer pathway navigation.

However, this dance between personalization and ethical considerations requires a graceful balance. Table 6 ("Challenges and Ethical Considerations") outlines the potential missteps, including data privacy, cultural differences, and bias. To ensure a flawless performance, we employ robust privacy safeguards, transparent data collection policies, and diverse training datasets for our algorithms. Furthermore, we incorporate individual preferences and cultural norms in our intervention design, empowering learners to control their emotional settings.

## VIII. EVALUATION

This pilot study unveils the intriguing potential of emotion-aware adaptive learning (Table 7). While lexicon-based emotion detection showed promise for boredom and frustration (72% and 68% accuracy, respectively), its limitations highlight the need for advanced techniques like machine-learning [12]. Notably, emotion-aware interventions significantly boosted engagement (25% more time on tasks, twice the forum participation) and learning outcomes (d = 0.60 improvement), echoing findings by [6]. Difficulty adjustments based on emotions proved impactful, but future research can expand interventions to personalized feedback [33] and adaptive pacing [32] to cater to a wider range of emotions and learning needs. As we navigate this exciting frontier, Table 7 underscores the paramount importance of ethical considerations like data privacy and user control, as outlined by[22].

## IX. DISCUSSION

### *A. Main Findings and Implications*

This pilot study demonstrates the promising potential of incorporating learner emotions through sentiment analysis in adaptive E-learning systems. Our findings highlight the feasibility of detecting boredom and frustration in learner forum posts using a lexicon-based approach, with significant correlations between detected emotions and engagement metrics. Moreover, learners in the experimental group, experiencing emotion-based content adaptation, exhibited increased engagement and achieved higher post-test scores compared to the control group. These results suggest that emotion-aware adaptive learning systems can personalize learning experiences, potentially leading to improved engagement and learning outcomes.

### *B. Mechanisms of Learning Improvement*

The observed improvement in learner engagement and performance in the experimental group attributed to several factors. Firstly, by addressing boredom through more challenging tasks or engaging resources, the system likely prevented cognitive disengagement and maintained learner attention. Secondly, timely support and resources provided to combat frustration might have mitigated negative emotions and helped learners overcome obstacles, fostering perseverance and knowledge acquisition. Further research employing multimodal data (e.g., facial expressions, physiological sensors) could shed light on the specific cognitive and emotional mechanisms underlying these observed learning improvements.

### *C. Limitations and Future Directions*

While this pilot study establishes the encouraging potential of emotion-based adaptation, limitations necessitate further investigation. The small sample size and single subject area restrict generalizability, demanding future research with larger and diverse populations in varied academic domains. Additionally, the lexicon-based approach, while moderately successful in detecting boredom and frustration, revealed inherent limitations in context and nuance. Moving forward, embracing more techniques that are advanced is crucial. Machine learning algorithms like SVMs and RNNs offer promising avenues for learning complex sentiment patterns, surpassing lexicon constraints. Integrating Named Entity Recognition (NER) can differentiate context-specific negatives (e.g., frustration with a concept) from general moods. Expanding sentiment lexicons with emotions like confusion, anxiety, and nuanced positive sentiment can enrich affect understanding. Acknowledging cultural norms and specific contexts demands training models on diverse datasets and incorporating sarcasm detection to avoid misinterpretations. By embracing these advancements, we can refine emotional detection capabilities, paving the way for even more personalized and emotionally responsive adaptive learning experiences, as exemplified by systems like EMASPEL (Figure 2).

## X. Conclusion

### A. *Emphasizing Promising Results*

Our pilot study vividly illustrates the viability and potential of incorporating learner emotions through sentiment analysis in adaptive E-learning. By leveraging a lexicon-based approach, we successfully detected boredom and frustration in forum posts, revealing significant correlations between these emotions and engagement metrics. Learners in the experimental group, where content was dynamically adapted based on their emotional cues, exhibited remarkable engagement. They spent more time on tasks, participated actively in forums, and demonstrated statistically significant improvement in post-test scores compared to their counterparts in the control group. These findings paint a compelling picture of the potential for emotion-aware learning systems to personalize experiences, leading to heightened engagement and potentially improved learning outcomes.

### B. *Acknowledging Limitations and Future Directions*

While this pilot study establishes the exciting potential of emotion-based adaptation, we acknowledge limitations that pave the way for future research. The relatively small sample size, focus on a single subject area, and reliance on a lexicon-based approach call for further investigation with larger populations, diverse subjects, and advanced sentiment analysis techniques like machine learning or deep learning. Additionally, ethical considerations necessitate rigorous attention to ensure responsible data collection and analysis of learner emotions. Despite these limitations, this study opens a vibrant portal for research and development of truly personalized and emotionally responsive E-learning systems. Future endeavors can explore the nuances of a wider range of emotions, expand adaptation beyond difficulty levels, and integrate multimodal data like facial expressions and physiological sensors for a more comprehensive understanding of learner affect.

### C. *Connecting to Broader Applications and Impact*

This pilot study contributes significantly to the burgeoning field of emotion-aware adaptive learning by displaying the potential of sentiment analysis to personalize learning experiences and cater to individual needs. As technology and research advance, incorporating learner emotions holds the power to revolutionize E-learning. By fostering deeper engagement, boosting intrinsic motivation, and empowering learners to thrive, we can not only contribute to individual success but also create a more inclusive and responsive learning landscape for all.

In conclusion, our research marks a pivotal moment in the trajectory of adaptive E-learning, where learner emotions take center stage. The positive outcomes observed in this study provide a solid foundation for further exploration and development of sophisticated emotion-aware systems. As we navigate this exciting frontier, the amalgamation of technological innovation and pedagogical insight has the potential to redefine the future of education, making it a deeply personalized and emotionally resonant journey for every learner.

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| Learner Emotion Detected | Sentiment Analysis Indicators (Lexicon-based) | Tone and Contextual Considerations | Adaptive Intervention (Experimental Group) |
|---|---|---|---|
| | - Misinterpretations of key concepts, requests for additional information | - Consider individual knowledge gaps and prior understanding. | - Rephrase key concepts: Provide different examples, analogies, and metaphors. |
| | - Increased use of hedging words ("maybe," "kind of") | - Confusion can impede cognitive processing and knowledge retention. | - Break down complex tasks: Smaller steps, incremental feedback, and mastery-based progression. |
| Confusion (Sarcastic) | - Irony, humor masking uncertainty, seemingly irrelevant questions | - Analyze tone and context beyond keywords. | - Offer non-judgmental support: Encourage direct questions without assuming understanding. |
| | - Exaggerated statements ("This is impossible!") | - May be seeking clarification or expressing frustration indirectly. | - Provide additional resources: FAQs, cheat sheets, glossary of terms. |
| | - Use of emojis or slang that express bewilderment | - Consider personality and communication style. | - Emphasize active learning: Encourage exploration, experimentation, trial and error. |
| Confidence | - Frequent contributions, positive language, volunteering for tasks | - May also mask anxiety or boasting. | - Offer more challenging content: Advanced topics, independent research projects. |
| | - Clear and concise explanations, insightful questions | - Could be a sign of mastery or overconfidence. | - Encourage leadership roles: Facilitate group discussions, mentor peers. |
| | - Use of emojis or slang that express excitement or enthusiasm | - Consider learning goals and motivation. | - Provide opportunities for self-reflection: Encourage metacognition, goal setting, progress tracking. |
| Anxiety | - Hesitant participation, worrying about mistakes, self-doubt | - May be hidden or expressed indirectly ("This is easy, right?"). | - Offer reassurance and encouragement: Focus on progress, effort, and learning goals. |
| | - Repetitive questions, requests for validation, seeking approval | - Can hinder engagement and cognitive processing. | - Provide low-stakes practice tasks: Quizzes, simulations, feedback before assessments. |
| | - Increased use of hedging words ("I think," "maybe") | - Anxiety can lead to avoidance behaviors and decreased risk-taking. | - Encourage peer support: Collaborative activities, online communities, buddy systems. |
| Boredom | - Short, infrequent forum posts (< 5 words) | - May indicate inattentiveness or disengagement, but consider sarcasm ("Easy!"). | - Offer interactive content: Mini-games, quizzes, polls related to current topic. |
| | - Simple language, repetitive sentence structures | - Could be genuine boredom or struggling with complex concepts. | - Suggest alternative learning paths: Simulations, case studies, creative tasks. |
| | - Increased use of negative sentiment words ("boring," "dull") | - Consider individual differences in learning styles and preferences. | - Increase collaboration opportunities: Group projects, discussion boards, peer review. |
| Frustration | - Exclamatory words ("stuck," "impossible"), negative comparisons | - Consider intensity and target ("too hard" vs. "frustrating for everyone"). | - Provide targeted hints: Break down complex steps, offer relevant examples. |
| | - Repetitive questions, requests for clarification, misunderstandings of concepts | - May be hidden or expressed indirectly ("This is easy, right?"). | - Offer scaffolding: Temporary support mechanisms, adaptive difficulty levels. |
| | - Increased use of punctuation (exclamation marks, question marks) | Frustration lead to cognitive overload and reduced problem-solving ability. | - Suggest alternative learning paths or pacing: Offer simpler explanations, allow for breaks or review. |
| Confusion | - Ambiguous phrases ("what does this mean?", "I'm lost") | - May be genuine confusion or sarcasm ("Is this even English?"). | - Offer detailed explanations: Use simpler language, visual aids (diagrams, animations). |

Table 2: Emotion Detection and Adaptive Interventions in E-learning

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Table 3: Performance Outcomes in Experimental and Control Groups

| Group | Pre-Test Scores (Mean) | Post-Test Scores (Mean) | Learning Gain (Mean) |
|---|---|---|---|
| **Experimental (Emotion-Aware Adaptation)** | 75 | 85 | 10 |
| **Control (Standard Adaptation)** | 75 | 80 | 5 |

Table 4: Sentiment Analysis Features for Emotion Detection

| Feature | Description | Example |
|---|---|---|
| **Lexical Features** | Presence of specific words or phrases associated with emotions | "boring," "frustrating," "confused," "excited" |
| **Syntactic Features** | Sentence structure and punctuation patterns that can reveal emotional tone | Increased use of exclamation marks, question marks, or hedges |
| **Semantic Features** | Meaning of words and phrases in context, considering sarcasm or irony | "Easy!" (could be genuine or sarcastic) |

Table 5: Learner Feedback on Adaptive Interventions

| Intervention | Positive Feedback | Negative Feedback | Suggestions for Improvement |
|---|---|---|---|
| **Interactive content** | "It made learning more fun and engaging." | "Sometimes it felt distracting from the main topic." | "Offer more variety in the types of interactive activities." |
| **Alternative learning paths** | "I liked having options when I was feeling stuck." | "It was sometimes hard to choose the right path." | "Provide clearer guidance on how to select the best path." |
| **Targeted hints** | "The hints were helpful when I was struggling." | "Some hints were too obvious or didn't provide enough information." | "Personalize hints based on individual learner needs and progress." |

Table 6: Challenges and Ethical Considerations

| Challenge | Description | Potential Solutions |
|---|---|---|
| **Data privacy and security** | Protecting learner data and ensuring ethical use of emotion detection | Robust privacy safeguards, transparent data collection policies, informed consent |
| **Cultural and individual differences** | Variations in emotional expression and interpretation across cultures and individuals | Consider cultural norms and individual preferences in emotion detection and intervention design |
| **Potential for bias** | Ensuring accuracy and fairness in emotion detection, avoiding reinforcement of stereotypes | Diverse datasets for training, careful evaluation of algorithms for bias, user-controlled emotion settings |

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Table 7: Comparative Table: Impact of Emotion-Aware Adaptation

| Aspect | Findings | Limitations | Future Directions |
|---|---|---|---|
| **Accuracy of Emotion Detection** | - Boredom: Lexicon-based accuracy 72%, comparable to [2]. Machine learning improved accuracy to 85%.<br>- Frustration: Lexicon-based accuracy 68%, similar to [13]. Machine learning increased accuracy to 80%. | - Limited to specific emotions (boredom, frustration).<br>- Lexicon rigidity struggles with sarcasm and context [13].<br>- Machine learning requires larger datasets and training time. | - Explore multi-modal data like eye-tracking and physiological sensors for wider range and context [12].<br>- Investigate transfer learning for faster and more efficient machine learning models. |
| **Impact on Learner Outcomes** | - Engagement: Emotion-aware group spent 25% more time on tasks and participated twice as much in forums compared to the control group.<br>- Learning Gains: Statistically significant improvement in post-test scores for the emotion-aware group (d = 0.60), aligning with [6]. | - Relatively small sample size limits generalizability.<br>- Single subject area (geometry) may not apply to all domains. | - Replicate study with larger and diverse populations across different subjects.<br>- Investigate long-term impact of emotion-aware learning on knowledge retention and transfer. |
| **Effectiveness of Adaptive Interventions** | - Difficulty Level Adjustments: Simplifying content for frustrated learners and challenging bored learners significantly improved engagement and performance. This aligns with [10]. (2017)'s dynamic framework. | - Limited to difficulty modifications.<br>- Does not address all emotional nuances (e.g., anxiety, confusion). | - Explore personalized feedback tailored to specific emotions [33].<br>- Implement adaptive pacing based on learner motivation and cognitive load [32] |
| **Ethical Considerations** | - Data privacy and security of learner emotions must be prioritized.<br>- Transparency and informed consent regarding data collection and analysis are crucial. | - Develop ethical guidelines for emotion-aware learning systems.<br>- Implement user control over data sharing and intervention preferences. | |