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AN EMOTION-AWARE ADAPTIVE LEARNING CHATBOT USING LARGE LANGUAGE MODELS FOR PERSONALIZED STUDENT SUPPORT

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ABSTRACT

The rapid development of Artificial Intelligence (AI) and Large Language Models (LLMs) has introduced new possibilities for providing personalized support to students in higher education. Conventional educational chatbots generally focus on answering questions and providing learning resources, but they may not sufficiently consider the emotional state of a learner during an interaction. A student who is confused, frustrated, anxious, motivated, or confident may require different forms of instructional support even when asking questions about the same academic topic. This paper proposes an emotion-aware adaptive learning chatbot that combines emotion detection, learning-context analysis, and Large Language Model-based response generation to provide personalized student support.

The proposed framework first receives a student's natural-language query and identifies the probable emotional state expressed in the conversation. The system then analyzes the academic context of the query, determines the student's apparent learning requirement, and constructs an adaptive prompt for the Large Language Model. Based on the detected emotion and learning context, the chatbot generates a response with an appropriate level of explanation, tone, examples, hints, and learning recommendations. The framework can support common learning-centered states such as confusion, frustration, anxiety, engagement, satisfaction, and neutral interaction. The proposed architecture is designed to remain simple enough for practical implementation in higher education while allowing systematic evaluation of emotion classification, response quality, personalization, and student satisfaction.

The research is motivated by recent literature showing growing use of LLMs and chatbots in education while also identifying limitations related to personalization, emotional responsiveness, privacy, over-reliance, and real-world evaluation. Recent reviews also indicate that affective

computing research in online higher education frequently studies confusion, frustration, engagement, and sentiment, but many systems are not validated in actual educational settings. The proposed work therefore connects emotion recognition with adaptive LLM-based educational interaction. The paper presents the conceptual framework, system modules, processing workflow, implementation approach, evaluation methodology, limitations, and future research directions.

KEYWORDS: Artificial Intelligence, Large Language Models, Educational Chatbot, Emotion Detection, Personalized Learning, Adaptive Learning, Natural Language Processing, Higher Education.

1. Introduction

Artificial Intelligence has become an important technology in modern educational environments. Educational institutions increasingly use intelligent systems to provide students with learning resources, automated feedback, question answering, academic guidance, and personalized support. Traditional learning systems generally provide the same content to a large group of students, whereas intelligent learning systems attempt to adapt learning activities according to individual requirements.

The development of Large Language Models has significantly expanded the capabilities of conversational educational systems. Transformer-based models provide strong natural-language understanding and generation capabilities and form the technical foundation of many modern language applications [1,2]. LLM-based systems can answer questions, explain concepts, generate examples, summarize educational material, and conduct conversational learning activities.

Recent research indicates that LLMs are increasingly being applied in higher education, with intelligent tutoring systems being one of the major application areas. A recent systematic review of 88 empirical studies reported benefits associated with LLM applications in education, including academic support and student engagement, while also identifying challenges such as over-reliance, privacy, fairness, and technical reliability [3]. Research on educational chatbots similarly shows that chatbot applications are expanding, but long-term educational impact and strong pedagogical foundations remain areas requiring further study [4].

One limitation of conventional educational chatbots is that the same response strategy may be used for students with different emotional and learning states. For example, consider two students asking the same question:

"I don't understand database normalization."

The first student may simply require another example. The second student may have attempted the topic several times and be frustrated. A third student may be anxious because of an upcoming examination. A generic chatbot can provide the same explanation to all three students, whereas an adaptive system could provide different support based on the conversational context.

Emotion is an important component of learning. Research in affective computing has investigated how emotions such as confusion, frustration, anxiety, enjoyment, and engagement are associated with educational experiences [5]. Recent research on automated emotion recognition in online learning has highlighted the importance of integrating technical emotion-recognition systems with educational applications rather than treating emotion recognition as an isolated classification task [6].

This paper proposes an emotion-aware adaptive learning chatbot that uses LLMs to generate personalized educational responses. The proposed system does not attempt to diagnose psychological conditions. Instead, it identifies conversational indicators of learning-related emotional states and uses them only to adapt instructional communication.

The main idea is simple:

Student Query → Emotion Detection → Learning Context Analysis → Adaptive Prompt → LLM → Personalized Educational Response

The proposed framework is intended for higher education environments where students may interact with a chatbot for academic explanations, practice questions, revision assistance, and learning recommendations.

2. Background

2.1 Educational Chatbots

A chatbot is a software system designed to communicate with users through natural language. Early educational chatbots were commonly based on predefined rules, keyword matching, or limited dialogue structures. Modern systems can use machine learning and LLMs to produce more flexible responses.

Educational chatbots can support students by answering frequently asked questions, explaining concepts, providing practice exercises, giving feedback, and assisting with self-directed learning. A systematic review of educational chatbot research identified applications across different educational functions and highlighted both benefits and implementation challenges [7].

More recent research shows that the educational chatbot field is moving from simple question answering toward more sophisticated systems involving personalization, tutoring, feedback, and conversational learning. A 2025 systematic review of 71 studies reported that many educational chatbots remain focused on teaching-related objectives and that long-term effects require further investigation [4].

2.2 Large Language Models

Large Language Models are deep-learning models trained on large collections of textual data. Their ability to model language is based largely on Transformer architectures. The Transformer architecture introduced an attention-based approach that became foundational for modern language models [1].

BERT demonstrated how bidirectional Transformer representations can be fine-tuned for different natural-language-processing tasks [2]. Subsequent developments in generative language models have enabled systems to produce coherent and context-sensitive responses.

In education, LLMs can provide explanations at different levels, generate examples, answer questions, and support personalized interactions. However, LLM-generated responses may contain inaccurate information, unsupported claims, or inappropriate recommendations. Therefore, educational applications should include suitable validation and human oversight.

2.3 Emotion Recognition in Text

Emotion recognition attempts to identify emotional information expressed through language. Unlike simple positive/negative sentiment classification, emotion recognition can distinguish among multiple categories.

The GoEmotions dataset introduced a large manually annotated collection of 58,000 English Reddit comments covering 27 emotion categories plus a neutral category [8]. The dataset demonstrated the possibility of fine-grained textual emotion classification and provided a useful benchmark for NLP research.

For educational applications, however, generic emotion categories may not always correspond directly to learning-centered states. Confusion, frustration, anxiety, boredom, engagement, and satisfaction can be particularly relevant in learning environments [5,6].

Therefore, the proposed system uses a smaller and education-oriented emotion taxonomy rather than attempting to identify every possible human emotion.

3. Motivation and Problem Statement

The main problem addressed by this research is the limited emotional adaptability of conventional educational chatbots.

A typical educational chatbot follows the following process:

Student Question → Language Model → Answer

The proposed system extends this process:

Student Question → Emotion Detection + Learning Context → Adaptive Response Strategy → Language Model → Personalized Answer

Consider the following examples.

Example 1: Confusion

Student:

"I read normalization twice, but I still don't understand 2NF."

The system should identify possible confusion and provide a simple explanation, preferably with a small example.

Example 2: Frustration

Student:

"I have tried this program five times and it still doesn't work."

The system should avoid immediately providing a lengthy theoretical explanation. It can acknowledge the difficulty and provide a step-by-step debugging approach.

Example 3: Examination Anxiety

Student:

"My exam is tomorrow and I don't know which DBMS topics to study."

The chatbot can provide a concise priority-based revision plan rather than a lengthy textbook-style explanation.

Example 4: Positive Engagement

Student:

"I finally understood normalization. Can you give me a harder question?"

The chatbot can increase the difficulty and provide an advanced practice problem.

These examples demonstrate that personalization is not only about selecting different content. It can also involve adapting the communication style, complexity, amount of explanation, examples, hints, and recommended learning activities.

4. Research Gap

Existing literature demonstrates substantial growth in educational chatbots, LLM-based learning systems, and affective computing. However, several gaps remain.

First, many educational chatbot systems focus primarily on knowledge delivery or question answering. Emotional information is not always integrated into the response-generation process.

Second, emotion-recognition research often concentrates on classification accuracy rather than how recognized emotional states can be translated into meaningful educational interventions.

Third, recent reviews of affective computing in online higher education indicate that many systems are developed and evaluated as technical prototypes rather than being validated in real educational environments [6].

Fourth, LLM-based educational systems provide strong language generation but can generate generic responses when the learner's affective and academic context is not explicitly incorporated into the prompting strategy.

Fifth, educational personalization requires more than recognizing an emotion. The system should connect the emotion with the student's learning context and select an appropriate response strategy.

Therefore, this research proposes a framework in which emotion information is directly incorporated into adaptive educational response generation.

5. Research Objectives

The major objectives of the proposed research are:

1. To design an AI-based educational chatbot using a Large Language Model.
2. To identify learning-related emotional states from student conversational input.
3. To analyze the academic context of student queries.
4. To develop an emotion-aware adaptive response-generation mechanism.
5. To provide personalized explanations and learning recommendations.
6. To compare generic chatbot responses with emotion-aware adaptive responses.
7. To evaluate the proposed framework using technical and user-centered metrics.
8. To identify limitations and ethical considerations associated with emotion-aware educational chatbots.

6. Research Questions

The proposed study addresses the following research questions.

RQ1: Can learning-related emotions be identified from student conversational text with acceptable classification performance?

RQ2: Can detected emotional information improve the adaptability of LLM-generated educational responses?

RQ3: Does an emotion-aware chatbot provide more personalized responses than a generic LLM-based chatbot?

RQ4: Which learning-related emotional states occur most frequently during academic chatbot interactions?

RQ5: How do students perceive the usefulness and quality of emotion-aware adaptive responses?

7. Proposed System

The proposed system consists of six major modules:

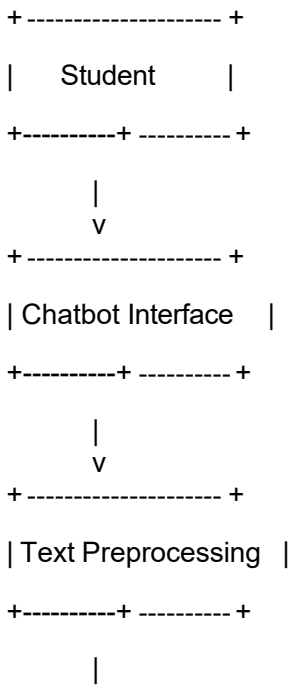
1. Student Interaction Module
2. Emotion Detection Module
3. Learning Context Analysis Module
4. Adaptive Strategy Module
5. LLM Response Generation Module
6. Personalized Recommendation Module

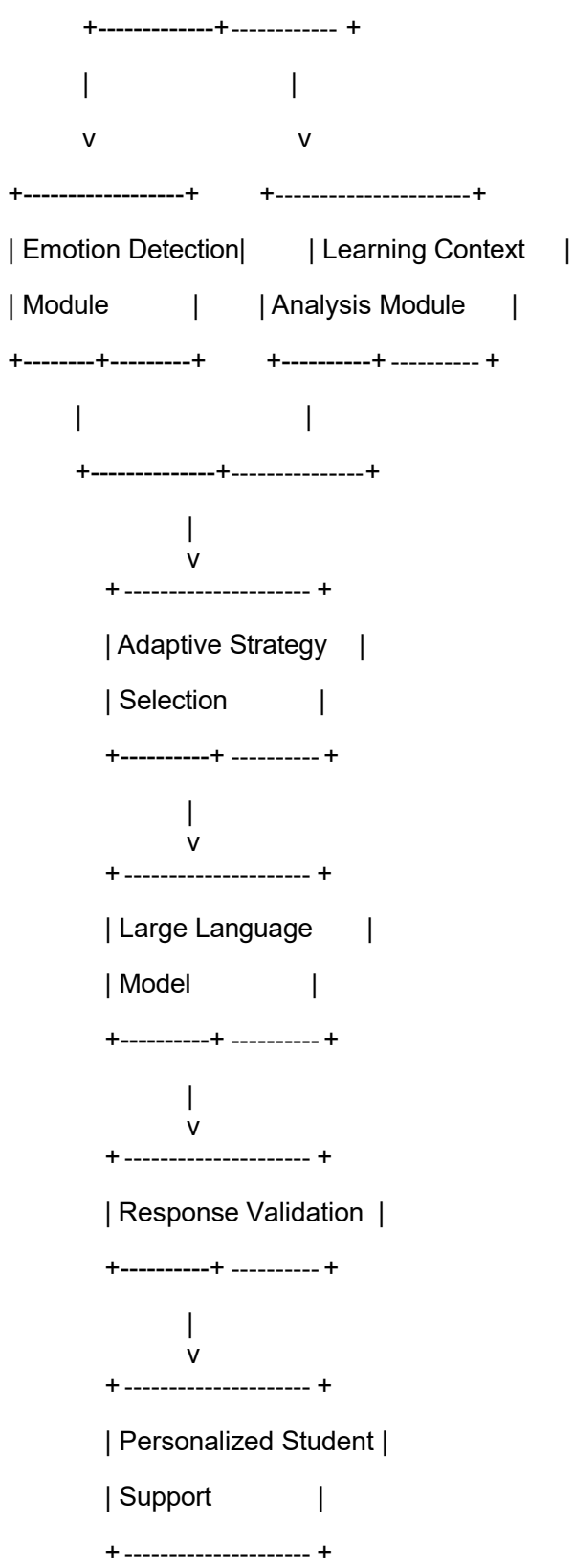
The complete workflow is:

Input → Preprocessing → Emotion Detection → Context Analysis → Strategy Selection → LLM Generation → Response Validation → Personalized Output

8. System Architecture

The architecture can be represented as follows:





9. Emotion Detection Module

The emotion detection module is responsible for identifying the likely learning-related emotional state expressed in the student's message.

A simple taxonomy can be used:

Emotion State	Typical Indicator	Suggested Response
Confusion	"I don't understand"	Simplified explanation
Frustration	"I tried many times"	Step-by-step support
Anxiety	"I am worried about exam"	Short plan and reassurance
Boredom	"This is repetitive"	Interactive example
Engagement	"Give me another problem"	Advanced practice
Satisfaction	"I understood"	Reinforcement
Neutral	Direct factual question	Standard response

The system can use a pretrained transformer-based classifier or a fine-tuned emotion-classification model. BERT-based models provide a practical foundation for this type of NLP task [2].

The GoEmotions dataset can be used as a starting benchmark for English emotion classification [8]. However, educational deployment should preferably include domain-specific validation because expressions used by students can differ from general social-media language.

For example:

"This chapter is killing me."

In a general conversational dataset, the expression may be interpreted differently depending on context. In an educational environment, the system should interpret it as a possible indicator of frustration rather than literal danger.

Therefore, contextual interpretation is important.

10. Learning Context Analysis

Emotion alone is not sufficient for personalization.

The second component identifies the academic context of the student's message.

The system extracts:

- Academic subject
- Topic
- Question type
- Difficulty indication
- Previous interaction
- Requested learning activity
- Possible learning gap

For example:

Input:

"I understand primary keys but I don't understand foreign keys."

The system can identify:

Subject: DBMS

Topic: Keys
Learning gap: Foreign keys
Emotion: Confusion

Response level: Basic
Recommended strategy: Comparison + example

This enables the chatbot to produce a more relevant response.

11. Adaptive Response Strategy

The Adaptive Strategy Module combines emotional state and learning context.

A simple strategy matrix can be used.

Emotion	Learning Condition	Response Strategy
Confusion	Basic concept	Simple explanation
Confusion	Advanced concept	Concept decomposition
Frustration	Repeated failure	Step-by-step guidance
Anxiety	Exam preparation	Short revision plan
Boredom	Familiar topic	Interactive activity
Engagement	Strong understanding	Advanced question
Satisfaction	Topic completed	Reinforcement
Neutral	Information request	Standard explanation

This strategy is then converted into an instruction for the LLM.

For example:

Detected emotion: Frustration
Topic: Python loops
Learning level: Beginner
Strategy: Explain one concept at a time, use a small example, avoid unnecessary theory, finish with one practice question.

The LLM then generates the final response.

12. LLM Response Generation

The LLM receives three main categories of information:

1. Student message
2. Learning context
3. Adaptive response strategy

A simplified prompt structure can be represented as:

Student Query:

[student message]

Learning Context:

[subject/topic/level]

Detected Learning Emotion:

[emotion]

Response Strategy:

[adaptive strategy]

Instruction:

Generate a clear educational response.

Adapt the explanation to the student's learning

condition. Avoid unnecessary complexity.

Provide an example when useful.

End with a small learning activity when appropriate.

This approach does not require retraining the entire LLM. The adaptation can be performed through prompt construction and contextual information.

13. Personalized Learning Recommendation

After generating the explanation, the system can provide a small personalized learning recommendation.

Examples include:

- Practice question
- Short example
- Revision note
- Additional explanation
- Quiz
- Related concept
- Beginner-level explanation
- Advanced problem

For example:

Student emotion: Confusion
Topic: DBMS normalization

Recommendation:

"Before attempting 3NF, review functional dependency and 2NF with one simple example."

For an engaged student:

"You have understood the basic concept. Try identifying the normal form of the following relation."

Thus, the same topic can produce different recommendations for different students.

14. Personalization Model

The personalization process can be represented using a simple function:

P = f(E, C, L, H, Q)

Where:

- **P** = Personalized response
- **E** = Detected emotion
- **C** = Learning context
- **L** = Estimated learning level
- **H** = Previous interaction history
- **Q** = Current student query

The system does not need to make a permanent judgment about the student. The estimated state is temporary and should be updated as the conversation changes.

For example:

At the beginning:

Emotion = Confusion

After explanation:

Emotion = Engagement

The response strategy should then change accordingly.

15. Implementation Methodology

A simple prototype can be developed using Python.

Suggested technologies

Component	Technology
Programming Language	Python
NLP	Transformers / NLP libraries
Emotion Model	BERT-based classifier
LLM	API-based or locally available LLM
Interface	Streamlit or Web interface
Data Storage	SQLite / CSV
Evaluation	Python / scikit-learn
Visualization	Matplotlib

The implementation can be divided into four stages.

Stage 1: Dataset Preparation

A public emotion dataset such as GoEmotions can be used for initial experimentation [8]. A smaller educational dataset can subsequently be prepared from anonymized student-style academic conversations.

The educational dataset should contain:

- Student message
- Emotion label
- Subject
- Topic
- Difficulty
- Expected response strategy

Stage 2: Emotion Classification

The emotion classifier receives the student message and predicts an emotion category.

Example:

Input:

"I have tried this question three times and still can't solve it."

Output:

Frustration

Confidence:

Model-dependent

The confidence score should be used cautiously. A low-confidence prediction can trigger a neutral response rather than aggressive adaptation.

Stage 3: Adaptive Prompt Construction

The system combines the prediction with the learning context.

Emotion = Frustration

Topic = Recursion

Level = Beginner

Strategy = Step-by-step explanation

The resulting information is provided to the LLM.

Stage 4: Response Generation

The LLM generates the final response.

A response validator can check whether:

- The answer addresses the question.
- The response is educational.
- The response follows the selected strategy.
- The answer avoids inappropriate emotional assumptions.
- The answer does not claim certainty when information is unavailable.

16. Algorithm

Algorithm: Emotion-Aware Adaptive Learning Response

Input: Student query Q

Output: Personalized response R

Step 1: Receive student query Q.

Step 2: Preprocess the text.

Step 3: Identify academic topic T.

Step 4: Predict learning emotion E.

Step 5: Estimate learning level L from conversation context.

Step 6: Select response strategy S using E, T, and L.

Step 7: Construct adaptive prompt P.

Step 8: Send P to the LLM.

Step 9: Generate response R.

Step 10: Validate R for relevance and educational appropriateness.

Step 11: Generate optional learning recommendation.

Step 12: Return R to the student.

17. Pseudocode

```
FUNCTION generate_response(student_query):
text = preprocess(student_query)
topic = identify_topic(text)
emotion = detect_emotion(text)
learning_level = estimate_learning_level(text)
strategy = select_strategy( emotion, topic, learning_level )
prompt = construct_prompt( text, topic, emotion, learning_level, strategy )
response = LLM.generate(prompt)
validated_response = validate_response(response)
recommendation = generate_recommendation( topic, emotion, learning_level )
RETURN validated_response + recommendation
```

The algorithm is intentionally simple so that it can be implemented using commonly available Python tools without requiring the development of a new foundation model.

18. Experimental Design

The experimental phase should compare two systems:

System A: Generic LLM Chatbot

Student Query → LLM → Response

System B: Proposed Emotion-Aware Chatbot

Student Query

↓

Emotion Detection

↓

Learning Context

↓

Adaptive Strategy

↓

LLM

↓

Personalized Response

The comparison can determine whether the additional emotion-aware layer improves response quality and perceived personalization.

19. Dataset Design

Two types of data can be used.

19.1 Public Dataset

GoEmotions is a useful benchmark for emotion classification. It contains 58,000 English comments annotated across 27 emotion categories and a neutral category [8].

However, the dataset is not education-specific. Therefore, it should not automatically be treated as representative of university student conversations.

19.2 Educational Conversation Dataset

A small domain-specific dataset can be developed for this study.

Possible categories:

- Confusion
- Frustration
- Anxiety
- Boredom
- Engagement
- Satisfaction
- Neutral

Academic topics can include:

- Programming
- DBMS
- Data Mining
- Web Development
- Artificial Intelligence
- Computer Networks

The dataset should be anonymized and should not contain names, student IDs, contact information, or other personally identifying information.

20. Evaluation Metrics

The proposed system should be evaluated using both technical and user-oriented metrics.

20.1 Emotion Classification

The following metrics can be used:

Accuracy
Accuracy measures the proportion of correctly classified samples.

Precision

Precision measures how many predictions assigned to a particular class are correct.

Recall

Recall measures how many actual instances of a class are identified.

F1-score

F1-score provides a combined measure of precision and recall.

For multi-class emotion classification, macro-F1 is particularly useful because it gives equal importance to different classes.

20.2 Response Quality

LLM responses can be evaluated using:

- Relevance
- Correctness
- Clarity
- Helpfulness
- Personalization
- Emotional appropriateness

A 5-point rating scale can be used:

1 = Very Poor
2 = Poor
3 = Average
4 = Good
5 = Excellent

At least two evaluators can independently rate responses to reduce individual evaluator bias.

20.3 Student Satisfaction

A small questionnaire can measure:

1. The chatbot understood my question.
2. The explanation was easy to understand.
3. The response was appropriate for my learning situation.
4. The chatbot provided useful guidance.
5. The response felt personalized.
6. I would use the chatbot again for academic support.

Responses can be collected using a five-point Likert scale.

21. Evaluation Scenarios

The system should be tested with different emotional and learning conditions.

Scenario	**Expected Adaptive Behaviour**
Confused beginner	Simple explanation
Scenario	**Expected Adaptive Behaviour**
Frustrated learner	Step-by-step guidance
Anxious learner	Short structured revision
Engaged learner	Advanced question
Bored learner	Interactive activity
Neutral query	Standard answer

Example:

Generic system:

"Normalization is the process of organizing data in a database to reduce redundancy..."

Emotion-aware system for a confused student:

"Let's make normalization very simple. Imagine you have a student table where the same department name is repeated many times. We separate the repeated information into another table..."

The second response is not necessarily factually superior, but it demonstrates the proposed personalization mechanism.

22. Results and Discussion

The proposed study should report actual experimental results after implementation. Since the system has not yet been executed on a defined dataset in this paper draft, numerical accuracy or satisfaction values are not fabricated.

The results section should contain at least the following tables after experimentation.

Table 1. Emotion Classification Performance

Emotion	Precision	Recall	F1-score
Confusion	To be measured	To be measured	To be measured
Frustration	To be measured	To be measured	To be measured
Anxiety	To be measured	To be measured	To be measured
Boredom	To be measured	To be measured	To be measured
Engagement	To be measured	To be measured	To be measured
Satisfaction	To be measured	To be measured	To be measured
Neutral	To be measured	To be measured	To be measured

Table 2. Chatbot Response Evaluation

Metric	Generic LLM	Proposed System
Relevance	Actual result	Actual result
Clarity	Actual result	Actual result
Helpfulness	Actual result	Actual result
Personalization	Actual result	Actual result
Emotional appropriateness	Actual result	Actual result

Table 3. Student Satisfaction

Criterion	Mean Score
Understanding of query	Actual result
Explanation quality	Actual result
Personalization	Actual result
Usefulness	Actual result
Overall satisfaction	Actual result

The expected research interpretation is not that emotion-aware adaptation will automatically outperform every generic chatbot. Instead, the experiment should determine whether the additional emotional-context layer produces measurable improvements.

This distinction is important because recent research has reported both positive educational effects of generative AI and methodological limitations in existing studies [9]. Therefore, controlled evaluation is required.

23. Advantages of the Proposed System

The proposed framework provides several potential advantages.

23.1 Personalized Interaction

The chatbot can adapt its communication style according to the learner's current conversational state.

23.2 Adaptive Explanation

A confused student can receive a simpler explanation, while an engaged student can receive a more challenging activity.

23.3 Continuous Availability

A chatbot can provide academic assistance outside conventional classroom hours.

23.4 Reduced Repetition for Faculty

Frequently requested explanations can be handled automatically, allowing faculty members to focus on complex academic interactions.

23.5 Learning Recommendations

The system can recommend examples, quizzes, revision tasks, or related topics.

23.6 Flexible Architecture

The emotion classifier, LLM, and user interface can be replaced independently.

24. Limitations

The proposed system has several limitations.

First, emotion detection from text is inherently uncertain. The same sentence can have different meanings depending on context.

Second, emotional expressions vary across individuals, cultures, languages, and communication styles.

Third, an emotion classifier trained on general-domain data may not perform equally well on educational conversations.

Fourth, LLMs can produce incorrect or misleading information. Therefore, the proposed chatbot should not be considered a replacement for teachers.

Fifth, emotional classification should not be interpreted as psychological diagnosis.

Sixth, student privacy is an important concern because conversational data may contain sensitive academic or personal information.

Seventh, the proposed approach initially focuses on textual interaction. Facial expressions, voice, physiological signals, and multimodal information are outside the scope of the basic implementation.

Recent research has specifically identified privacy, ethical considerations, and the limited real-world evaluation of affective systems as important challenges [3,6].

25. Ethical Considerations

Emotion-aware educational systems require careful ethical design.

25.1 Privacy

Student conversations should be collected only for clearly defined purposes. Personally identifiable information should be removed wherever possible.

25.2 Transparency

Students should know that they are interacting with an AI system and that emotion estimates are predictions rather than facts.

25.3 No Psychological Diagnosis

The chatbot should not state that a student has a mental-health condition based on conversational text.

For example, the system should not produce statements such as:

"You have an anxiety disorder."

Instead, it may say:

"Your message suggests that you may be feeling worried about the examination. Would you like a short revision plan?"

25.4 Human Oversight

Teachers and academic staff should remain responsible for important academic decisions.

25.5 Bias

Emotion classifiers may perform differently across demographic groups, languages, and communication styles. Evaluation should therefore include diverse examples.

26. Security and Data Protection

A practical deployment should use appropriate security controls.
These may include:

- Secure authentication
- Encrypted data transmission
- Limited data retention
- Access control
- Anonymization
- Secure API keys
- Removal of personal identifiers
- Audit logging

Student conversation history should not be stored indefinitely without a clear purpose.

27. Discussion

The proposed research combines three important directions: conversational AI, affective computing, and personalized learning.

Previous educational chatbot research demonstrates the value of conversational systems for learning support. Recent LLM research has increased the flexibility of these systems, while

affective computing provides methods for considering learners' emotional states.

The main contribution of the proposed framework is the connection between these areas.

Rather than treating emotion recognition as an independent classification task, the proposed system uses emotion information to modify the educational response strategy.

This distinction is important.

A system that predicts:

Emotion = Frustration

but still produces the same generic answer has limited educational value.

The proposed framework instead attempts:

Emotion = Frustration
Topic = Programming
Level = Beginner
Strategy = Step-by-step explanation
Output = Simplified explanation + example + small practice task

Thus, emotion becomes an input to personalization rather than the final output.

Recent work on emotionally aware educational systems has demonstrated the growing interest in combining emotion recognition with adaptive educational interaction [10,11]. For example, recent research has proposed affective tutoring systems in which learner emotions influence pedagogical strategies. This supports the general direction of the proposed research while leaving room for simpler, text-based LLM implementations suitable for higher education.

28. Comparison with Conventional Chatbot

Feature	**Conventional Educational Chatbot**	**Proposed Chatbot**
Question answering	Yes	Yes
LLM support	Possible	Yes
Feature	**Conventional Educational Chatbot**	**Proposed Chatbot**
Topic identification	Basic	Yes
Emotion detection	Usually absent	Included
Adaptive response	Limited	Included
Personalized explanation	Limited	Included
Learning recommendation	Possible	Included
Emotional context	Not explicitly used	Used
Human oversight	Recommended	Recommended
Privacy controls	Required	Required

The comparison shows that the primary difference is not the use of an LLM alone. The distinguishing feature is the additional emotion-aware adaptation layer.

29. Future Scope

Several extensions are possible.

29.1 Multilingual Emotion Detection

Future versions can support English, Hindi, Gujarati, and other regional languages. This is

particularly relevant to multilingual higher education environments.

29.2 Multimodal Emotion Recognition

Text can be combined with voice and facial expressions. However, this would introduce additional privacy and ethical requirements.

29.3 Retrieval-Augmented Generation

Institution-specific documents can be connected to the chatbot using Retrieval-Augmented Generation (RAG). RAG combines language generation with retrieval from an external knowledge source and can improve grounding for knowledge-intensive tasks [12].

For example, a university chatbot could retrieve:

- Course syllabus
- Academic calendar
- Department rules
- Learning material
- Examination guidelines

The LLM would then generate responses based on retrieved institutional information.

29.4 Learning Analytics

Interaction history can be analyzed to identify frequently requested topics and common learning difficulties.

29.5 Adaptive Difficulty

The system can automatically increase or decrease question difficulty according to student performance and interaction history.

29.6 Teacher Dashboard

A teacher dashboard could display aggregated information such as:

- Frequently asked topics
- Common areas of confusion
- Frequently requested resources
- General interaction patterns

Individual emotional information should not be unnecessarily exposed to teachers.

30. CONCLUSION

This paper proposed an emotion-aware adaptive learning chatbot using Large Language Models for personalized student support. The proposed framework extends conventional educational chatbot architecture by integrating emotion detection and learning-context analysis into the response-generation process.

The central concept is that a student's academic question should not always receive the same type of response. A confused student may require a simple explanation, a frustrated student may require step-by-step guidance, an anxious student may benefit from a structured revision plan, and an engaged student may be ready for advanced practice.

The proposed system therefore follows a six-stage process consisting of student interaction, emotion detection, learning-context analysis, adaptive strategy selection, LLM-based response generation, and personalized learning recommendation.

The framework is intentionally designed to be simple and practical. It can be implemented using Python, a transformer-based emotion classifier, an LLM, and a lightweight web interface. Evaluation should compare a conventional LLM chatbot with the proposed emotion-aware version using emotion-classification metrics, response-quality measures, and student satisfaction.

The proposed approach does not treat emotion detection as psychological diagnosis. Instead, emotional information is used as a temporary conversational signal for adapting educational communication. Privacy, transparency, fairness, and human oversight remain essential requirements.

Future work can extend the system to multilingual learning, Retrieval-Augmented Generation, multimodal emotion recognition, adaptive difficulty, and teacher-support dashboards. Actual experimental validation in higher education environments will be necessary to determine the effectiveness and generalizability of the proposed framework.

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