International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 15 Issue 3, March-2026

EchoConnect: A Real-Time Emotion-Aware Intelligent Tutoring System Using Transformer-Based Analysis

Shruti Navnath Tate[1], Rutuja Bhagvat Chavan[2], Sanika Satyawan Umape[3], Vaishnavi Shivaji Gadhave[4], Mahamadshoyab M. Attar[4], Deepa M. Radhod[6]

[1-6]Department of Computer Science & Engineering, Yashoda Technical Campus Satara, Dr. Babasaheb Ambedkar University, Maharashtra, India

ABSTRACT

Intelligent Tutoring Systems (ITS) have improved personalized learning, but many existing systems still focus mainly on cognitive performance while overlooking the learner's emotional state. Since emotions such as confusion, frustration, and engagement directly influence learning effectiveness, incorporating affective awareness can improve tutoring quality and learner interaction. This paper presents EchoConnect, a real-time emotion-aware intelligent tutoring system that dynamically adapts instructional responses based on detected learner emotions. The system uses a DistilRoBERTa-based transformer model for text-based emotion classification and integrates a large language model through the Groq API to generate adaptive tutoring responses with low latency. Learner emotions are mapped into four educational categories: ENGAGED, CONFUSED, FRUSTRATED, and NEUTRAL, which guide pedagogical strategies such as step-by-step explanations, encouragement, or advanced problem-solving. EchoConnect also maintains session-level context to support multi-turn personalized learning interactions. The proposed architecture combines a React frontend, FastAPI backend, and MongoDB persistence layer to enable scalable and responsive real-time tutoring. Experimental evaluation achieved approximately 84% emotion classification accuracy with consistent adaptive response quality and stable multi-turn interaction performance. The results demonstrate the feasibility of integrating affective computing and real-time adaptive tutoring within modern AI-driven educational systems.

Keywords: Affective Computing, Intelligent Tutoring Systems, Transformer Models, Emotion Detection, Adaptive Learning, Real-Time Processing.

INTRODUCTION

Intelligent Tutoring Systems (ITS) have become increasingly important in digital education by providing personalized learning and automated instructional support. Most existing tutoring systems focus mainly on academic performance and often ignore the learner's emotional state during the learning process. Emotions such as confusion, frustration, and engagement significantly affect learning effectiveness. Human tutors naturally adapt their teaching style based on these emotional cues, but many AI-based tutoring systems still lack this capability.

Recent advancements in Natural Language Processing (NLP) and transformer-based models have made real-time text-based emotion detection more effective. At the same time, large language models (LLMs) can generate interactive and context-aware educational responses, enabling more adaptive learning experiences.

This paper presents EchoConnect, a real-time emotion-aware intelligent tutoring system designed to improve personalized learning interaction. The system uses a DistilRoBERTa-based model to detect learner emotions and dynamically adapts tutoring responses based on emotional state. EchoConnect categorizes learner emotions into ENGAGED, CONFUSED, FRUSTRATED, and NEUTRAL states and generates adaptive responses using the Groq API.

LITERATURE REVIEW

Sr. No.	Paper Title & Year	Methodology Used	Key Contribution	Limitations

1	"Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge" (1994)	Knowledge Tracing	Tracks learner understanding over time	Does not consider learner emotions
2	"Affective Computing" (1997)	Emotion-Aware Computing	Introduced emotion recognition in intelligent systems	Not focused on educational tutoring
3	"Attention Is All You Need" (2017)	Transformer Architecture	Improved contextual language understanding	High computational requirements
4	"DistilBERT: Smaller, Faster, Cheaper and Lighter" (2020)	Distilled Transformer Model	Enables fast and lightweight NLP inference	Slight reduction in accuracy
5	"Towards an Affect-Sensitive AutoTutor" (2007)	Emotion-Aware Tutoring	Demonstrated adaptive tutoring using learner emotion	Limited scalability and older techniques
6	"ChatGPT for Good? On Opportunities and Challenges of LLMs for Education" (2023)	Large Language Models	Highlighted educational applications of LLMs	Limited emotional personalization

METHODOLOGY

The EchoConnect system follows a real-time emotion-aware tutoring approach for personalized learning. The system consists of a React frontend, FastAPI backend, MongoDB database, and AI-based emotion detection and tutoring modules.

First, the learner interacts with the tutoring interface by submitting textual queries. The input text is processed using a DistilRoBERTa-based transformer model to detect the learner's emotional state. The detected emotions are categorized into ENGAGED, CONFUSED, FRUSTRATED, and NEUTRAL.

Based on the detected emotion, the system dynamically adjusts the tutoring strategy. Confused learners receive step-by-step explanations, frustrated learners receive supportive guidance, engaged learners receive advanced explanations, and neutral learners receive balanced instructional responses.

The tutoring responses are generated using a large language model through the Groq API. Session history and learner interactions are stored in MongoDB to maintain contextual continuity across multiple interactions.

The complete workflow includes user input, emotion detection, adaptive response generation, session storage, and real-time response delivery. The system is designed to provide low-latency interaction suitable for intelligent tutoring applications.

RESULTS AND DISCUSSION

Fig. 1. EchoConnect Dashboard Interface

The dashboard provides an overview of learner activity, including session count. The interface enables users to monitor learning progress in real time.

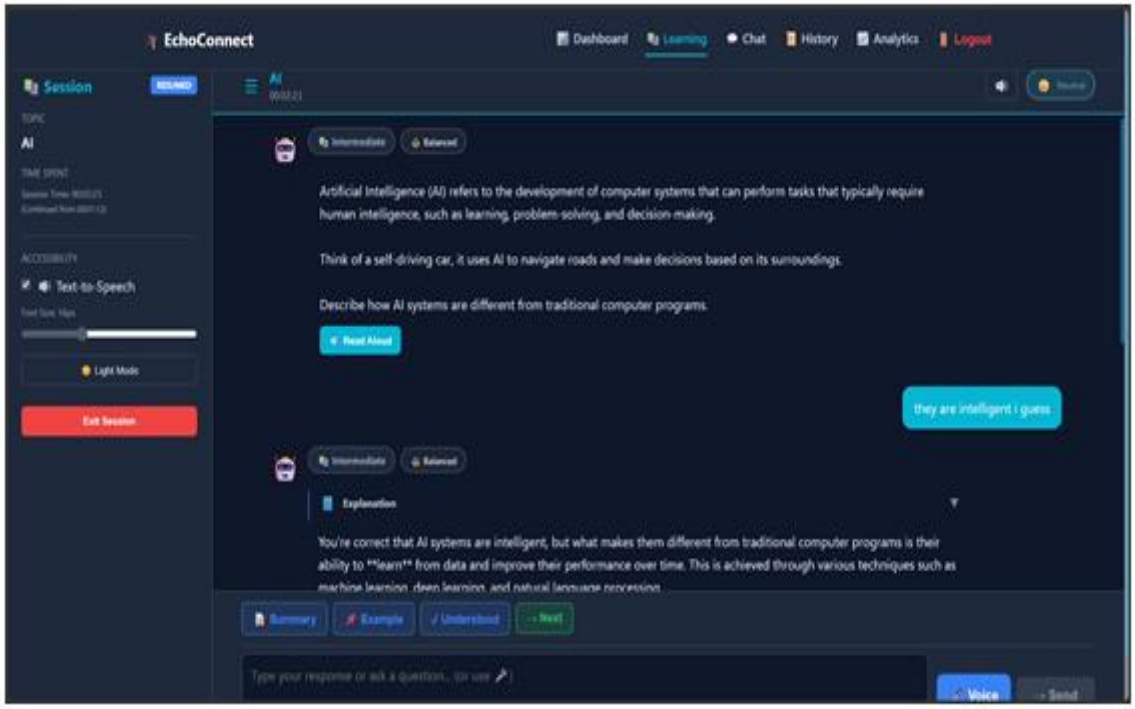

Fig. 2. Real-Time Adaptive Tutoring Interaction

The system dynamically generates tutoring responses based on learner input and detected emotional state. The interface supports interactive learning through contextual explanations, follow-up questions, and adaptive instructional guidance.

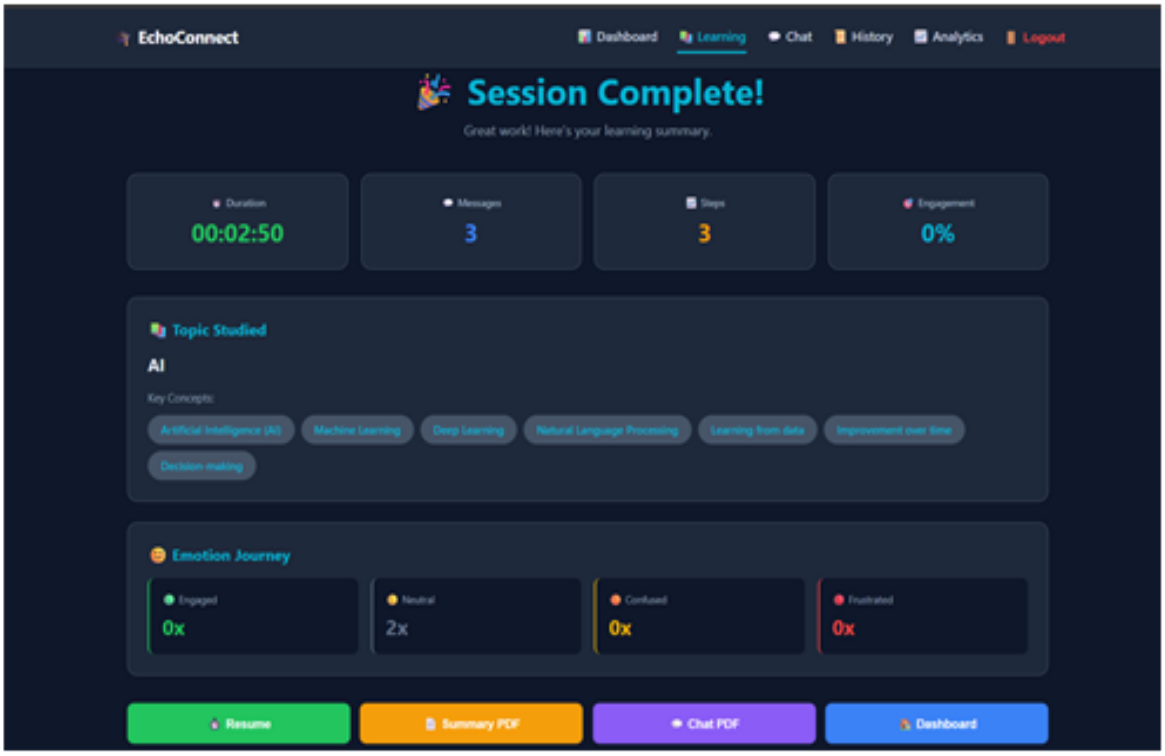

Fig. 3. Session Summary and Emotion Analytics

The session summary screen displays learning duration, interaction statistics, studied topics, and emotion distribution throughout the session. This helps visualize learner engagement and emotional progression during tutoring interactions.

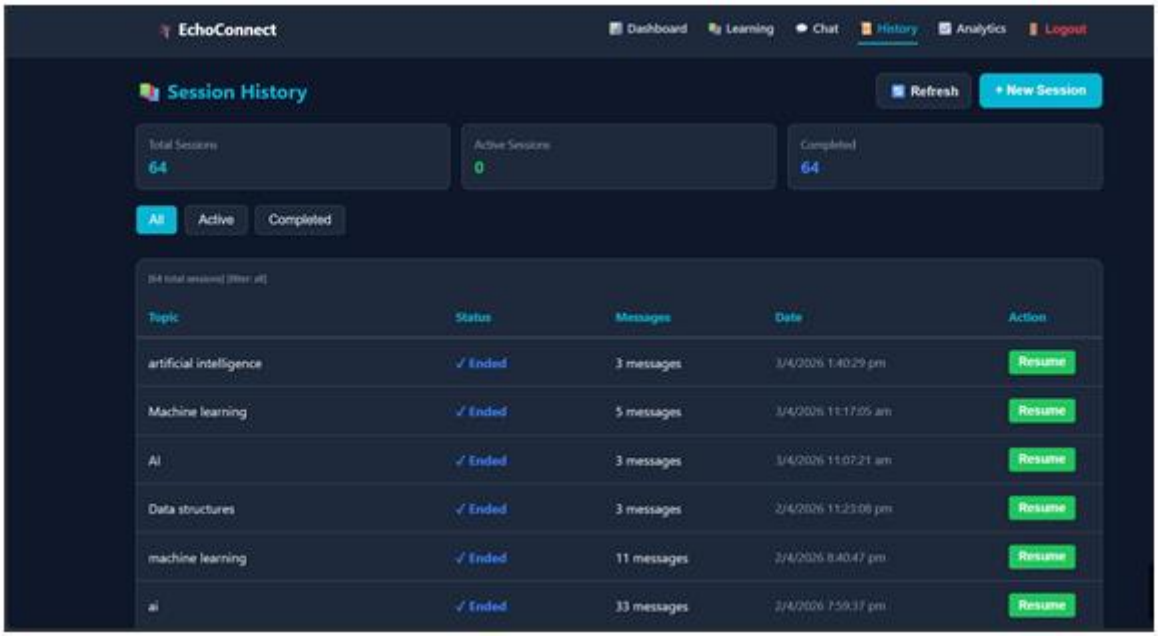

Fig. 4. Session history

CONCLUSION

In conclusion, EchoConnect presents a practical approach for integrating affective computing with intelligent tutoring systems. Instead of providing uniform responses, the system dynamically adapts instructional behavior according to learner emotions, creating a more personalized learning experience.

The integration of transformer-based emotion detection, adaptive tutoring strategies, and large language model response generation enables real-time emotionally aware interaction. The system successfully demonstrated stable performance, effective emotion classification, and context-aware tutoring behavior.

Although the current implementation has limitations such as limited emotion categories and dependency on external APIs, the project demonstrates the potential of emotion-aware tutoring systems in modern education.

Future improvements may include multimodal emotion recognition, multilingual support, and enhanced learner modeling for more advanced personalization

REFERENCES

[1] J. R. Anderson and A. T. Corbett, “Knowledge Tracing: Modeling the Acquisition of Procedural Knowledge,” *User Modeling and User-Adapted Interaction*, vol. 4, no. 4, pp. 253–278, 1994.
[2] R. W. Picard, *Affective Computing*. Cambridge, MA, USA: MIT Press, 1997.
[3] A. Vaswani et al., “Attention Is All You Need,” in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017, pp. 5998–6008.
[4] V. Sanh et al., “DistilBERT: A Distilled Version of BERT: Smaller, Faster, Cheaper and Lighter,” in *Proceedings of the 5th Workshop on Energy Efficient Machine Learning and Cognitive Computing*, 2020, pp. 77–86.
[5] S. D’Mello, A. Graesser, and R. W. Picard, “Towards an Affect-Sensitive AutoTutor,” *IEEE Intelligent Systems*, vol. 22, no. 4, pp. 53–61, 2007.
[6] E. Kasneci et al., “ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education,” *Learning, Media and Technology*, vol. 48, no. 2, pp. 1–19, 2023.
[7] C. A. Tomlinson, *The Differentiated Classroom: Responding to the Needs of All Learners*, 2nd ed. Alexandria, VA, USA: ASCD, 2014.