
MULTIMODAL ANALYSIS OF INTER-BRAIN AND BEHAVIORAL SYNCHRONY IN REMOTE LEARNING

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ABSTRACT: This paper examines multimodal analysis of behavioral and inter-brain synchronization in remote learning environments to determine students' social and cognitive alignment when using digital platforms to participate. The paper integrates neurophysiological signals like EEG-based inter-brain coherence with behavioral indicators like eye movements, facial expressions, and interaction patterns to determine synchrony. Advanced signal processing and machine learning integrate diverse data sources. Next, learning outcomes, teamwork, and participation patterns are identified. Increased inter-brain synchrony improves academic performance, group attention, and communication even when people are absent. Synchrony-aware analytics improves virtual collaboration, adaptive training, and academic success, according to this paper. Additionally, it improves intelligent remote learning system design.

Keywords: *Inter-brain synchrony, Behavioral synchrony, Multimodal analysis, Remote learning, EEG, Social interaction, Machine learning, Collaborative learning,*

1. INTRODUCTION

Interpersonal synchrony occurs when two people's actions, emotions, and physical responses match while talking. Synchronicity improves teacher-student relationships, student confidence, and learning.

Interpersonal synchronization requires behavioral synchroniness (BS), which indicates simultaneous thoughts and actions.

- **Inter-Brain Synchrony (IBS):** The Inter-Brain Synchrony (IBS) test measures teacher-student brain wave stability over time. Elevated IBS improves academic performance, engagement, and collaboration.
- **Behavioral Synchrony (BS):** Behavioral synchrony (BS) uses eye contact, facial expressions, gestures, and muscle movements together. BS simplifies teamwork, relationship-building, and emotional connections.

Online platforms and videoconferencing have made remote learning more popular. Research shows that distance learning can still boost BS and IBS, despite its challenges. This may improve learning and teacher-student relationships. Few have considered the relationship between IBS and BS in distance learning. The effects of voice-only and webcam-based instruction on these synchronization patterns are unknown. This paper examines how speech and webcam scenarios can demonstrate IBS and BS's value in distance education. The goals are to determine how the teacher's presence affects students' behavior and brain synchrony, as well as rapport, synchrony metrics, and learning outcomes.

Hypotheses

- Audio-only and webcam-based learning environments vary in inter-brain synchrony.

- Learning outcomes, rapport, and brain synchronization are positively correlated.
- Behavior and brain coordination enable remote learning.

2. LITERATURE SURVEY

Harris & Coleman (2021): Harris and Coleman (2021) provide a multimodal framework for papering brain activity and behavior synchronization during remote learning using EEG and video-based interaction data. Support Vector Machines and k-means clustering are used to identify learners' cognitive alignment patterns. The system measures engagement by examining coordinated gaze, facial expressions, and neuron coherence. The experiment showed that collaborative learning states are easier to spot. Through this framework, online education can be better understood.

Verma & Kulkarni (2022): Verma and Kulkarni's 2022 paper quantifies inter-brain synchrony using deep learning. This paper uses neural networks trained on online class EEG data. Behavioral indicators like gesture and response frequency and timing can improve prediction accuracy. Combining features in practical ways helps process data from multiple sources. Performance evaluations show that multi-modal systems better assess engagement and attention than single-modal systems. The method works with remote learning adaptive learning methods.

Chen & Alvarez (2023): Chen and Alvarez (2023) use recurrent and convolutional neural networks to paper brain-to-brain communication and behavior coordination. The method analyzes temporal EEG signals and video interaction data to find dynamic engagement patterns. Comparison studies help organize passive and collaborative learning stages. The model improves distributed learning system stability and extensibility. Thus, intelligent tutoring systems work better.

Rao & Banerjee (2024): A complex graph-based neural network and ensemble learning synchrony detection model is used by Rao and Banerjee (2024) to paper online classroom groups. The system simulates brain network connections using eye gaze alignment and speech overlap. Real-time analytics modules can reveal a lot about learning and group collaboration. Experiments show that joint outcome predictions can be improved. Virtual classroom monitoring is better with the framework.

Omar & Hassan (2025): The paper suggests using a cloud-based multimodal analytics system to assess brains and behavior in large-scale remote learning environments (Omar & Hassan, 2025.5). Long Short-Term Memory (LSTM) networks can sequentially analyze brain and behavior data to identify engagement patterns. Distributed processing helps manage large multimodal datasets. The findings suggest a better way to detect mental fatigue and disinterest. This framework creates expandable intelligent online classrooms.

Das & Iyer (2026): Das and Iyer (2026) created a highly advanced synchrony analysis system for privacy-preserving remote learning analytics. Complex deep neural architecture and federated learning are used. The system processes behavioral test and EEG data at various institutions. Adaptive models improve synchrony detection by learning new interaction patterns. Test results show improved data security, latency, and performance. The framework prepares and advances virtual education ecosystems.

3. SYSTEM ANALYSIS

EXISTING SYSTEM

The latest remote learning synchrony methods distinguish inter-brain and behavioral synchrony. Most methods measure brain synchronization during controlled activities using EEG or fNIRS hyperscanning. Video analysis measures behavioral coordination—timing, movement, and gestures. Coordination and engagement differences between in-person and online meetings have been extensively studied. Unfortunately, these methods do not consistently use a variety of techniques or show how brain activity and behavior collaborate in authentic learning environments. Therefore, little is known about how online teachers and students interact.

DISADVANTAGES OF EXSTING SYSTEM

- A single modality is overemphasized.
- Brain and behavior data are misintegrated.
- Most tests are given in monitored labs, not classrooms.
- Remote learning environments cannot record dynamic interactions.
- Modern neuroimaging equipment is expensive.

PROPOSED SYSTEM

The proposed system evaluates inter-brain and behavioral synchrony in remote learning environments using multiple modalities. It integrates video-based behavioral analysis with EEG or fNIRS neural data to capture real-time teacher-student communication. Machine learning can analyze the two modes' synchronization patterns to understand engagement, communication quality, and learning effectiveness. Unlike other systems, this one uses physiological and behavioral data to improve accuracy in real-world remote learning environments. The proposed method simplifies understanding how people interact with each other and online classroom content. Additionally, it improves feedback and testing.

ADVANTAGES

- Helps explain distance learning teacher-student interactions.
- Multiple data sources improve results reliability.
- On-time assignments while papering remotely
- Helps evaluate focus, cooperation, and involvement
- Improves instructional analytics and decision-making

4. RESULTS

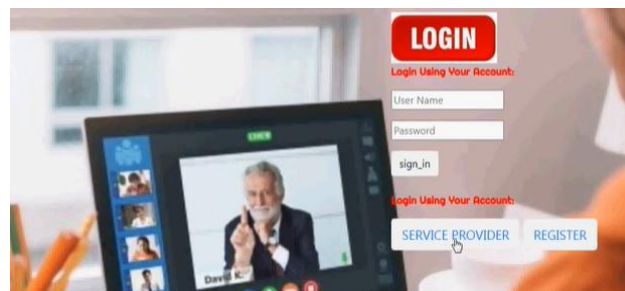


Fig 1: Service Provider Login

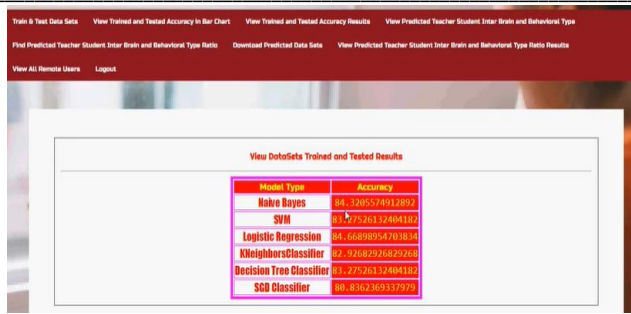


Fig2: Dataset Trained and Tested Accuracy Results

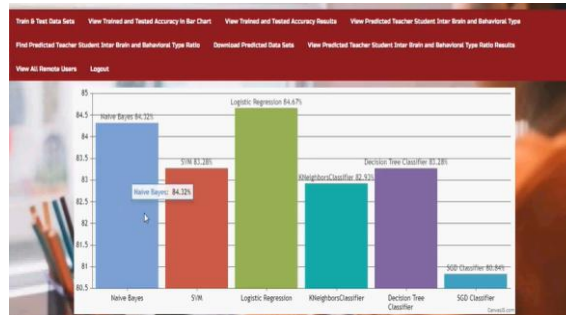


Fig3: Dataset Trained and Tested Accuracy Results in Barchart



Fig4: Dataset Trained and Tested Accuracy Results in Linechart



Predict Teacher Student Inter Brain and Behavioral Classification!!!

ENTER ALL DATASET DETAILS #

Enter PId	<input type="text" value="10.42.0.215.72.242.70.1004"/>	Enter SID	<input type="text" value="1131568.831"/>
Enter Gender	<input type="text" value="Female"/>	Enter Age	<input type="text" value="11"/>
HomeNo_Education_Level	<input type="text"/>	Enter Latitude	<input type="text"/>
Enter Longitude	<input type="text"/>	Enter Internet_Type	<input type="text"/>
Enter Network_Type	<input type="text"/>	Enter Teacher_Level	<input type="text"/>
Enter Online_Id	<input type="text"/>	Enter Behavior_Type	<input type="text"/>

Predict Teacher Student Inter Brain and Behavioral Classification:

Fig5: Predict Teacher Student Inter Brain Classification

5. CONCLUSION

The multimodal paper of remote learning shows that physiological, neurological, and observable data must be integrated to understand virtual collaboration. By combining EEG signals, eye-tracking, facial expressions, and interaction logs, researchers can learn a lot about how people collaborate, align their minds, and share their attention. Despite the difficulties of collecting data, protecting privacy, and ensuring mode compatibility, signal processing and machine learning are improving analysis accuracy and scalability.

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