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A Review of Multimodal Data-Driven Evaluation Research on Blended Teaching Models

Minling Zhu[1,a,*], Wangbo Su[1,b], Dongning Wu[2,c], Hongbo Huang[1,d]

[1]*College of Computer Science, Beijing Information Science and Technology University, Beijing, China*

[2]*China Wisdom Engineering Association, Beijing, China*

[a]*zhuminling@bistu.edu.cn*, [b]*771134260@qq.com*, [c]*wudongning@chinawea.org.cn*, [d]*hhb@bistu.edu.cn*

**Corresponding author*

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Abstract: Blended teaching has become the new normal in higher education, yet its evaluation remains challenging due to the distribution of learning behaviors across online and offline spaces. Multimodal learning analytics offers a new paradigm for precise evaluation. This paper systematically reviews research on multimodal data-driven evaluation of blended teaching, examining theoretical foundations, data sources, methodologies, applications, and challenges. The review reveals that multimodal evaluation has evolved from single-dimensional behavioral measurement toward comprehensive assessment encompassing cognition, emotion, behavior, and social interaction. Methods have shifted from traditional questionnaires to machine learning and multimodal fusion, while evaluation content has moved from outcome-oriented to process-oriented assessment. Knowledge graphs are emerging as tools for knowledge visualization and cognitive diagnosis within multimodal frameworks. However, technical bottlenecks in data fusion, insufficient model interpretability, and ethical concerns remain critical challenges. Future research should focus on developing interpretable models, advancing educational multimodal fusion algorithms, and establishing frameworks that balance effectiveness with ethical considerations.

1. Introduction

Blended teaching, which integrates the strengths of traditional face-to-face instruction and online learning, has become the new normal in post-pandemic education. However, the implementation of blended teaching presents new challenges for evaluation: learning behaviors are distributed across both online and offline spaces, making it difficult for traditional single-measure evaluation methods, predominantly based on final examination scores, to comprehensively capture students' learning processes and outcomes. Hou et al. [1], through a systematic review of 47 empirical studies conducted between 2015 and 2024, found that the effectiveness of blended teaching exhibits significant heterogeneity, as effect sizes are moderated by design quality rather than by the model itself. This implies that evaluation cannot remain at the level of model-based judgment but must extend to the fine-grained characterization of teaching processes.

In this context, the emergence of Multimodal Learning Analytics (MMLA) offers new possibilities for blended teaching evaluation. MMLA integrates multiple data sources, including video, audio, physiological signals, and digital interaction logs, to achieve comprehensive capture and precise analysis of learning processes. Guerrero-Sosa et al. [2], in a comprehensive review of 177 empirical studies, noted that MMLA, by integrating diverse data sources, can provide a richer view of learning processes than unimodal approaches. Introducing multimodal data technologies into blended teaching evaluation represents not merely an upgrade in technical means but a fundamental paradigm shift from experience-driven to data-driven assessment, and from outcome-oriented to process-oriented evaluation.

This paper focuses on the core theme of "multimodal data-driven evaluation of blended teaching models". The research framework is shown in Figure 1, which progressively elaborates on the theoretical foundations, multimodal data foundations, methodological framework, application practice and effectiveness validation, and challenges and future prospects. The aim is to provide a reference for the theoretical construction and practical optimization of blended teaching model evaluation.

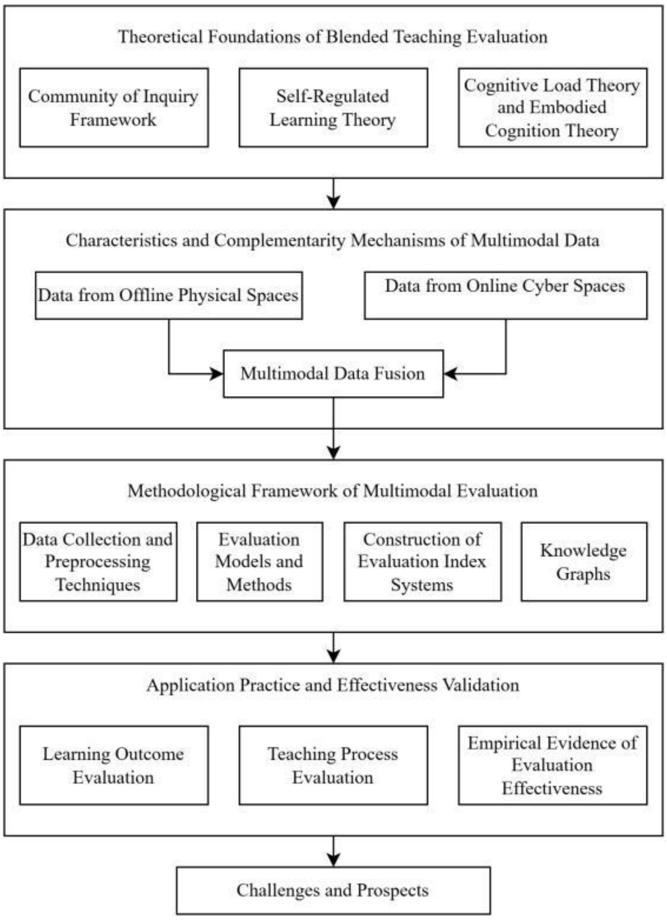

Figure 1: Structural Diagram of the Review on Multimodal Assessment in Blended Teaching.

2. Theoretical Foundations of Blended Teaching Evaluation

Multimodal data-driven evaluation of blended teaching models is not merely a combination of technical tools; it is supported by solid educational theories.

2.1. Community of Inquiry Framework

The Community of Inquiry (CoI) framework, proposed by Garrison et al., is one of the most widely cited theoretical frameworks in the field of blended teaching evaluation. The CoI model posits that meaningful deep learning experiences occur at the intersection of three core elements: social presence, teaching presence, and cognitive presence. Social presence refers to learners' ability to project themselves authentically, express emotions, and engage in social interaction within a community; teaching presence refers to the design, facilitation, and direction of cognitive and social processes by instructors; and cognitive presence refers to the extent to which learners construct meaning through sustained reflection and dialogue.

The significance of CoI theory for multimodal evaluation lies in the fact that the three presences can be measured through different modalities of data. Social presence can be captured through textual analysis of forum discussions and emotional prosody in audio; teaching presence can be characterized through instructors' verbal behaviors, movement trajectories, and the temporal sequencing of teaching activities; and cognitive presence can be assessed through learners' test performance, knowledge graph mastery, and the quality of higher-order thinking tasks. The study by Yu et al. [3], grounded in the CoI framework, empirically verified that multimodal blended teaching significantly outperforms traditional blended teaching across all three dimensions of social presence, teaching presence, and cognitive presence. This empirical finding demonstrates that when multimodal technologies serve the deep learning structure delineated by CoI, evaluation gains theoretical explanatory power rather than remaining mere data aggregation.

2.2. Self-Regulated Learning Theory

Self-Regulated Learning (SRL) theory focuses on learners' metacognitive, motivational, and behavioral processes of planning, monitoring, and reflecting on their own learning. In blended teaching environments, learner autonomy is significantly enhanced, making SRL ability a critical variable influencing learning outcomes and simultaneously providing an important analytical dimension for evaluation.

MMLA's contribution to SRL assessment lies in the following. Traditional SRL research has largely relied on self-report data from questionnaires and interviews, whereas multimodal data can capture behavioral traces of SRL, such as when learners pause videos, whether they repeatedly review difficult content, and how they plan their learning paths within learning management systems. These behavioral traces provide an objective evidentiary basis for assessing SRL processes, enabling formative evaluation to more precisely diagnose the effectiveness of learning strategies within the SRL framework.

2.3. Cognitive Load Theory and Embodied Cognition Theory

Cognitive load theory offers another important analytical lens for multimodal evaluation. The theory distinguishes among intrinsic, extraneous, and germane cognitive load. In blended teaching scenarios, multimodal data, particularly physiological signals, provide new possibilities for real-time assessment of cognitive load. For instance, changes in pupil diameter from eye-tracking data can serve as physiological indicators of cognitive load. This enables evaluation to move beyond post-hoc testing for inferring learning difficulty, allowing for dynamic monitoring of cognitive load states during the learning process.

In contrast to cognitive load theory's emphasis on internal psychological processes, embodied cognition theory highlights the active role of the body in cognitive processes. The theory posits that learning occurs not only in the brain but also through interaction with the physical environment, the use of gestures, and bodily movement. In multimodal evaluation, this theory manifests in the emphasis on physical-space data such as body posture, gestures, and movement trajectories. The indicators of teacher movement trajectory and learner movement trajectory incorporated in the study by Li et al. [4] exemplify the concrete application of embodied cognition perspectives in evaluation practice. Movement patterns themselves embody important information about instructional design and learning engagement.

In summary, multimodal evaluation does not simply analyze whatever data are available; rather, guided by the aforementioned learning theories, it determines which data best reflect key learning processes according to the explanatory frameworks of these theories. Theory imbues data with educational meaning, and data provide empirical support for theory. The two are mutually reinforcing and together constitute the cognitive foundation of multimodal evaluation.

3. Data Foundations of Blended Teaching Evaluation

3.1. Data Sources in Blended Teaching Scenarios

Blended teaching scenarios are characterized by cross-spatiality. Learning activities occur simultaneously in offline physical spaces and online cyber spaces. This determines that the data required for evaluation must span both spaces. Zhang et al. [5] classified multimodal learning analytics data in blended learning into five categories: basic information data, learning physiological data, human-computer interaction data, learning resource data, and learning context data. This classification framework provides a systematic reference for data collection in blended teaching evaluation.

Specifically, data from offline physical spaces are primarily acquired through sensors such as cameras, microphones, and wearable devices, including learners' facial expressions, body postures, verbal interactions, and movement trajectories. Data from online cyber spaces derive from learning management system logs, online discussion content, and quiz completion records. Fan et al. [6], from a multimodal data-driven perspective, constructed a blended learning evaluation index system, emphasizing that the organic integration of both types of data constitutes a panoramic record of the learning process.

3.2. Characteristics and Complementarity Mechanisms of Multimodal Data

The core value of multimodal data lies in their complementarity. A single modality of data can only reveal one facet of the learning process, whereas the fusion of multiple modalities enables a holographic understanding of learning states. For example, learners' quiz accuracy rates may not reflect their true level of comprehension, but when combined with facial expressions and eye-tracking trajectories, evaluators can more accurately determine whether learners have genuinely mastered the knowledge.

Multimodal data also exhibit cross-validation and transformability. Data from different sources can corroborate the same conclusion, enhancing the reliability of evaluation. Physical-space data can be transformed into storable and analyzable digital data through technological means. This complementarity, cross-validation, and transformability constitute the methodological foundation of multimodal evaluation. Mu et al. [7], in their systematic review, characterized data fusion in terms of four mechanisms: complementarity, cross-validation, fusion, and transformability. This framework provides a clear theoretical tool for understanding the data logic of multimodal evaluation.

4. Methodological Framework of Multimodal Evaluation

4.1. Data Collection and Preprocessing Techniques

The first step in multimodal evaluation is data collection. Current research has developed diverse collection methods: visual data are acquired through cameras and computer vision technologies; auditory data through microphones and speech recognition technologies; physiological data through wearable devices such as smart bands, eye-trackers, and EEG devices; and interaction data through automatic logs from learning management systems. The review by Guerrero-Sosa et al. [2] systematically categorized data collection modalities into five types: visual, auditory, physiological, interaction logs, and environmental data. The review noted that while visual data remain the most widely used modality, the combination of physiological signals and interaction logs is an emerging trend.

Data preprocessing is a critical step in the evaluation pipeline. Data from different sources have varying temporal granularities and formats, requiring cleaning, synchronization, annotation, and dimensionality reduction before they can enter the analysis phase. Zhang et al. [5] constructed a multimodal learning analytics process for blended learning that covers the complete chain from data collection and cleaning-fusion to analytical modeling and decision feedback. Guerrero-Sosa et al. [2] further noted that the quality of the preprocessing stage directly determines the effectiveness of subsequent modeling, particularly regarding cross-modal temporal alignment. Different modalities of data may be collected at different sampling frequencies; without precise alignment, the fused features will lose temporal semantic consistency.

4.2. Evaluation Models and Methods

The methodology of multimodal evaluation has evolved from traditional statistical analysis toward machine learning and deep learning.

At the modeling technique level, the review by Guerrero-Sosa et al. [2] systematically catalogs the various techniques used in MMLA, including classical machine learning methods such as Support Vector Machines, Decision Trees, and Random Forests, as well as deep learning approaches including CNNs, LSTMs, and Transformers. The systematic review by Mehfooza et al. [8] indicates that in blended learning scenarios involving multimodal educational data, the predictive accuracy of neural networks, temporal graph models, and advanced machine learning models such as Transformers can reach 82% – 91%. Specifically, ensemble learning models such as XGBoost perform well in course completion prediction, while Transformer networks can achieve 91.5% accuracy in weekly learning performance forecasting.

At the fusion strategy level, multimodal evaluation encompasses three primary approaches. The first is "many-to-one" fusion, in which multiple data modalities jointly measure the same learning indicator to improve measurement accuracy. The second is "many-to-many" fusion, in which multiple data modalities correspond to multiple learning indicators respectively to enrich information dimensionality. The third is multimodal data cross-validation, which enhances the credibility of conclusions through cross-verification across different data sources. Mu et al. [7], in their systematic review of 346 MMLA articles published between 2017 and 2020, demonstrated that these three fusion strategies each have their applicable scenarios, with "many-to-one" fusion primarily used to improve measurement accuracy and "many-to-many" fusion to enrich information dimensionality.

4.3. Construction of Evaluation Index Systems

The construction of evaluation index systems is a critical link in moving multimodal evaluation from technology to practice. Li et al. [4], targeting the open education OMO smart teaching environment, developed a classroom analysis index system covering three dimensions: instructional design, teaching implementation, and teaching effectiveness. Within this framework, the instructional design dimension focuses on the proportional duration of teaching models and the sequencing of teaching activities. The teaching implementation dimension focuses on the proportional duration of teacher-student speech and movement trajectories. The teaching effectiveness dimension focuses on learner engagement curves and in-class quiz performance.

At a more micro level, multimodal evaluation has also begun to attend to the quantification of specific cognitive and affective indicators. Yu et al. [3], through the CoI framework, verified that multimodal blended teaching significantly outperforms traditional blended teaching across social presence, teaching presence, and cognitive presence. Additionally, some studies have constructed an evaluation model of university faculty teaching engagement in blended teaching environments from a multimodal data-driven perspective, encompassing five evaluation dimensions: cognitive engagement, emotional engagement, social engagement, behavioral engagement, and technological engagement. The development of these index systems has moved multimodal evaluation from a "data-driven" approach toward a "goal-oriented" model.

4.4. The Role of Knowledge Graphs in Evaluation

Knowledge graphs, as structured knowledge representation tools, are gradually being integrated into multimodal evaluation systems and are playing an increasingly important role in cognitive diagnosis and knowledge structure assessment.

From the perspective of evaluation functions, the contribution of knowledge graphs to blended teaching evaluation is primarily reflected in three aspects. First, visualization of knowledge structures. Course knowledge graphs organize scattered knowledge points into a semantic network of entities, relationships and attributes, enabling learners' knowledge structures to be visually presented. Teachers can quickly locate the overall knowledge weaknesses of a class through knowledge graphs, and students can also identify their own knowledge gaps with the help of graphs. This visualization itself constitutes a form of formative assessment. Learners do not need to wait until examinations to know where they have not mastered the content. Second, precision in cognitive diagnosis. Traditional tests can only provide a total score and cannot distinguish between a lack of knowledge and inaccurate recall. Knowledge graphs support tracking at the knowledge point level. Each knowledge point can be independently assigned prerequisite, subsequent, and associative relationships. A learner's mastery of a particular knowledge point can be cross-validated through performance on related knowledge points. The study by Xie et al. [9], based on this principle, achieved refined tracking of 672 core knowledge points through knowledge graphs, enabling teachers to precisely locate each student's knowledge weaknesses and thus achieving a granularity shift in evaluation from class average scores to individual knowledge graphs. Third, navigation and evaluation of learning paths. Knowledge graphs support nonlinear learning path planning. Students can navigate autonomously along the relational edges of knowledge graphs during preview or review, rather than passively following chapter order. The process data of this autonomous navigation, such as which node students start from and which paths they take to reach target nodes, becomes an important basis for evaluating their metacognitive abilities and learning strategies.

It is noteworthy that the combination of knowledge graphs and multimodal data is giving rise to new forms of evaluation. Traditional knowledge graphs have relied largely on test data to update node states. In multimodal evaluation frameworks, however, facial expressions, eye-tracking trajectories, and physiological signals can provide richer evidence for the mastery states of knowledge graph nodes. For example, when a student spends an unusually long time at a particular node in the knowledge graph, or repeatedly reviews video content associated with that node, the system can combine their facial expressions of confusion with subsequent test performance to comprehensively determine whether there is a comprehension difficulty at that node, rather than making a judgment based solely on test scores. This multimodal fusion diagnosis of "behavioral traces plus physiological signals plus test performance" significantly improves the accuracy and timeliness of cognitive assessment.

5. Application Practice and Effectiveness of Multimodal Evaluation

5.1. Learning Outcome Evaluation

The most direct application of multimodal evaluation is predicting and improving student learning outcomes. By integrating multiple types of data, including behavioral records, academic performance, and social learning indicators, predictive models can identify students at risk of dropout in advance or forecast course completion. The comprehensive analysis by Mehfooza et al. [8] revealed a clear hierarchy of predictive strength. Engagement consistency is the strongest predictor. Students with at least four LMS logins per week are 3.2 times more likely to master the course. Assessment behavior patterns rank second in predictive power. Mere forum post counts show weak correlation with learning outcomes, with truly predictive value residing in "deep posts" that include citations or reflective questions. This finding has direct implications for the selection of evaluation indicators. Evaluation should not stop at counting what was done but should focus on how and when it was done.

At the course level, multimodal evaluation has also achieved positive results. Xie et al. [9], based on a knowledge graph-based blended teaching practice in histology and embryology, demonstrated that the experimental group's knowledge point mastery rate (88.89%) was significantly higher than that of the control group (75.56%), with total course scores improving from 78.5 to 86.9 points. This indicates that multimodal evaluation is not merely a measurement tool but also possesses formative functions that promote learning. Students in the experimental group also showed significantly higher self-reported improvements than the control group in dimensions such as knowledge construction efficiency, problem solving ability and practical application ability. This demonstrates that when knowledge graphs are embedded in multimodal evaluation systems as cognitive diagnostic tools, evaluation is no longer merely a summative judgment at the end of learning but continuously provides cognitive feedback throughout the learning process, thus truly fulfilling the formative function of promoting learning. The multimodal data-driven blended learning evaluation system for university students constructed by Fan et al., through the integration of process-oriented evaluation, value-added evaluation, and outcome-based evaluation, achieved precise assessment of student learning.

5.2. Teaching Process Evaluation

Another significant value of multimodal evaluation lies in real-time diagnosis of the teaching process. Through intelligent analysis of multidimensional data, including teacher-student speech ratios, movement trajectories, and student engagement curves, teachers can obtain more refined teaching feedback than traditional classroom observations. The study by Li et al. [4] pointed out that multidimensional index systems, through mutual interpretation and corroboration among indicators, effectively enhance the explanatory power and operability of analytical results.

At the practical level, multimodal blended teaching models supported by smart teaching platforms such as Xuexitong have constructed a complete evaluation loop encompassing four modules: teaching resources, learning platforms, interactive feedback, and evaluation methods [10]. Qu [11] further noted that multimodal blended teaching supported by digital-intelligence platforms not only enables the diversified presentation of teaching resources and multimodal interaction in teaching activities but, more importantly, through real-time data analysis of online and offline learning, renders the learning process, evaluation methods, and feedback systems more rational and assessment more precise.

5.3. Empirical Evidence of Evaluation Effectiveness

Existing empirical studies demonstrate that multimodal evaluation has significant effectiveness advantages in blended teaching scenarios. The review by Guerrero-Sosa et al. [2], covering 177 empirical studies, found that multimodal learning analytics technologies can effectively enhance the accuracy and explanatory power of teaching evaluation. Another systematic review [7] also indicated that predictive models based on multimodal data fusion significantly outperform unimodal models in accuracy.

However, the realization of effectiveness is not automatic. The dual-track evaluation reform practice in histology and embryology laboratory teaching by Yang et al. [12] provides a valuable counterexample. Traditional drawing-based evaluation, due to interference from the intervening variable of drawing proficiency, failed to accurately reflect students' true level of knowledge mastery. This study demonstrates that even within the same course, if the design of the evaluation method fails to effectively eliminate interfering variables, the validity of the evaluation will be compromised. This finding reminds us that the advancement of technical means does not automatically translate into evaluation precision. Evaluation design must aim to eliminate interference and directly target core competencies.

6. Challenges and Prospects

6.1. Technical Bottlenecks

Multimodal evaluation still faces several technical bottlenecks. The first is the difficulty of data synchronization and alignment. Different modalities of data have varying temporal granularities and sampling frequencies, and achieving precise temporal alignment is a fundamental challenge of data fusion [7]. The second is insufficient model interpretability. Although deep learning models offer high predictive accuracy, their "black box" nature makes it difficult for teachers to understand the logic behind evaluation results, thereby weakening the operability of evaluative feedback [2]. Additionally, temporal performance decay is a challenge. Mehfooza et al. [8] found that model performance decays at a rate of 0.82% per week, necessitating regular retraining. It is worth noting that technical bottlenecks are often not isolated. The precision of temporal alignment directly affects model predictive accuracy, while insufficient model interpretability is closely related to the complexity of fusion strategies. This implies that technical breakthroughs require systematic solutions rather than piecemeal technical patches.

6.2. Ethical and Privacy Considerations

Multimodal evaluation involves the collection and analysis of multiple types of sensitive data, including facial, vocal, and physiological information, making privacy and ethical issues unavoidable. Ensuring informed consent for data collection, protecting student data security, and avoiding algorithmic bias against non-traditional student populations are all urgent ethical issues to be addressed. The review by Guerrero-Sosa et al. [2] specifically noted that predictive models exhibit significant accuracy bias for non-traditional learners such as working adults. A cross-national study found accuracy disparities of 14.2% for working adult learners and 11.7% for first-generation college students. This serves as a reminder that the technical design of multimodal evaluation must incorporate fairness considerations inherently, rather than deferring ethical review until after the system has been developed. Ethical issues are not merely compliance issues but also validity issues. If a particular group is systematically marginalized in data collection and model training, the evaluation results lose explanatory power for that group.

6.3. Future Research Directions

Looking ahead, research in this field should focus on the following directions. First, develop explainable artificial intelligence technologies so that evaluation models can not only produce results but also articulate their rationale. Current research has attempted to embed interpretability tools such as SHAP and LIME into MMLA systems, finding that this can increase faculty trust in and adoption of models by 41% [8]. Second, explore privacy-preserving technologies such as federated learning to enable cross-institutional multimodal evaluation while safeguarding data security. Third, promote the evolution of evaluation from technology overlay to deep integration, establishing evaluation frameworks that are deeply integrated with teaching practice. Fourth, strengthen teacher data literacy training so that educators can effectively understand and apply multimodal evaluation results to improve teaching. The survey by Li [13] found that while students' awareness of and interest in blended teaching have increased, there remains considerable room for growth. Teacher data literacy improvement and student adaptation to new models are two sides of the same coin. Building an evaluation system without cultivating user data literacy will significantly diminish system effectiveness.

7. Conclusion

Multimodal data-driven evaluation of blended teaching models represents an epochal shift in educational assessment from experience-based judgment to data-driven intelligence. This systematic review demonstrates that the field has developed a complete methodological framework encompassing multi-source data collection, multimodal fusion analysis, and multidimensional index system construction, showing significant application value in learning outcome prediction and teaching process diagnosis. It is noteworthy that knowledge graphs, as tools for knowledge structure visualization and cognitive diagnosis, are gradually being integrated into this framework, providing a structural perspective from individual knowledge points to the overall network for assessing learners' knowledge mastery and filling the gap in cognitive structure analysis that traditional multimodal evaluation has lacked. However, technical bottlenecks, insufficient interpretability, and ethical risks remain real obstacles to large-scale adoption. Future research must seek a balance between technological innovation and educational wisdom, ensuring that multimodal evaluation truly serves as an effective tool for promoting teaching improvement and student development, rather than merely a technical exercise.

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