Multimodal Quantification Mechanism and Intervention for Student Cognitive Engagement in Blended Classrooms

Authors: Tian Yuan, Nie Xinxiao, Liu Hainuo, Liu Zhongjian, Fang Min, Zhang Qi, Tian Yuan

Date: 2024-07-17T00:00:00+00:00

Abstract

Cognitive engagement, defined as the degree of learners' mental effort and application of cognitive strategies, constitutes a critical factor influencing learning outcomes in blended learning. However, existing assessments of student cognitive engagement suffer from pronounced subjectivity and unimodal limitations, hindering the clear elucidation of cognitive engagement levels in blended classrooms and constraining instructional improvements. This study proposes to investigate the quantification and intervention of cognitive engagement in blended classrooms through integrated mathematical modeling, laboratory experiments, and teaching-tracking quasi-experiments. The research will develop a multimodal quantitative representation model for cognitive engagement, formulate enhancement strategies, create a blended instructional design framework for higher education, and devise an integrated teaching-research tool for cognitive engagement identification and intervention, thereby providing theoretical and practical support for improving the quality and efficiency of blended learning.

Full Text

Preamble

Multi-modal Quantitative Assessment Mechanism and Intervention of Learners' Cognitive Engagement in Blended Classrooms

TIAN Yuan, NIE Xinxiao, LIU Hainuo, LIU Zhongjian, FANG Min, ZHANG Qi
(Key Laboratory of Adolescent Cyberpsychology and Behavior (CCNU), Ministry of Education;
Key Laboratory of Human Development and Mental Health of Hubei Province;
School of Psychology, Central China Normal University, Wuhan 430079, China)

Abstract: Cognitive engagement refers to the degree of learners' mental effort and application of cognitive strategies during learning, representing a critical factor influencing learning outcomes in blended teaching. However, previous assessments of student cognitive engagement have suffered from issues such as strong subjectivity and single-modality measurement, making it difficult to clarify learners' cognitive engagement levels in blended classrooms and constraining improvements in teaching effectiveness. This study aims to combine mathematical modeling, laboratory experiments, and quasi-experimental teaching tracking to investigate the quantification and intervention of cognitive engagement in blended teaching contexts. We will establish a multi-modal quantitative representation model for cognitive engagement in blended classrooms and develop strategies to enhance it, forming a blended teaching solution for higher education and creating an integrated teaching-research tool for cognitive engagement identification and intervention. The findings are expected to provide theoretical and practical support for improving the quality and efficiency of blended teaching.

Keywords: blended classroom, cognitive engagement, multi-modal measurement indices, intervention strategies
Classification Codes: B849: G44

1 Problem Statement

As the Internet becomes increasingly integrated into human life, higher education has fully harnessed the substantial advantages of information technology, gradually evolving toward digitalization and intelligence. In February 2023, the "Overall Layout Plan for Digital China Construction" issued by the Central Committee of the Communist Party of China and the State Council explicitly stated that in the education sector, we must accelerate the innovative application of digital technology and vigorously implement the national education digitalization strategy. Driven by both national policy and global educational development trends, educational digitalization has entered a stage of prosperous development. As Minister of Education Huai Jinpeng noted, "Digital technology is a ladder to improve education quality." The appropriate use of digital technology to empower teaching method reform can provide powerful momentum for enhancing education quality.

Blended Teaching is a novel instructional model that integrates network technology into traditional face-to-face teaching (Müller & Mildenberger, 2021), defined as the deliberate integration of face-to-face and online learning experiences (Garrison & Kanuka, 2004). It enables seamless fusion of face-to-face and technology-mediated learning (Porter et al., 2014), combining the presence and immersion of traditional face-to-face instruction (Jusoff & Khodabandelou, 2009) with the flexibility and adaptability of online learning, significantly enhancing students' learning abilities, interpersonal skills, and learning outcomes (Bredow et al., 2021). The "Implementation Opinions on the Construction of First-Class Undergraduate Courses" (Jiao Gao [2019] No. 8) vigorously promotes the construction of online-offline blended first-class courses, making blended teaching the new normal in higher education. Optimizing blended teaching supported by artificial intelligence to drive educational innovation is a key pathway to achieving digital transformation and intelligent upgrading of education in China. However, realizing optimal blended teaching requires effective integration of learning resources, methods, teaching strategies, and activities, giving full play to teachers' guiding role while ensuring students' principal status. The complexity of elements and diversity of learning environments in blended settings have long posed significant challenges to improving blended teaching effectiveness (Lightner & Lightner-Laws, 2016). From the perspective of multi-element interaction, optimizing blended teaching strategies to enhance students' cognitive engagement is a critical path to achieving optimal blended teaching outcomes (Zhou & Han, 2018).

Cognitive engagement refers to learners' mental effort during learning and the process of applying appropriate learning strategies to master knowledge or skills (Shi et al., 2021; Liu et al., 2022), serving as an important antecedent variable affecting student achievement (Xie et al., 2020). As the most difficult-to-obtain deep-level implicit information under the complex concept of learning engagement with the strongest predictive power for learning outcomes (Tian & Wu, 2022), how to accurately represent learners' cognitive engagement levels and propose appropriate enhancement strategies has become a focal issue for educational science researchers. Numerous studies have shown that cognitive engagement is closely related to learners' performance and learning outcomes during the learning process (Miller, 2015; Rotgans & Schmidt, 2011; Walker et al., 2006), and is influenced by environmental and individual factors. Environmental factors such as teaching media use, teaching pace, and feedback methods interact with learners' individual factors to cause fluctuations in cognitive engagement (Lu et al., 2021; Appleton et al., 2006). In blended teaching contexts, abundant learning resources and complex learning environments affect learners' cognitive engagement, though relevant research remains scarce.

Moreover, in quantifying cognitive engagement, studies have predominantly used subjective retrospective reporting, which is heavily influenced by subjective factors and time lags, making it difficult to reflect changes in cognitive engagement across different activity contexts (Jiang et al., 2018). Teachers cannot obtain individual and group-level cognitive engagement data, greatly constraining targeted improvements in teaching effectiveness. Therefore, investigating quantification methods and enhancement strategies for learners' cognitive engagement in blended classrooms holds important theoretical and practical significance for improving blended teaching effectiveness.

Blended teaching comprises an online self-study phase and a face-to-face classroom phase. The online self-study phase typically involves students independently learning online resources to acquire prerequisite knowledge, while the face-to-face classroom phase is teacher-led and student-centered, helping students exercise and consolidate knowledge to achieve internalization (Li & Zhao, 2004). On one hand, enhancing learners' cognitive engagement must consider both improving self-study processes and optimizing classroom instruction, making it necessary to discuss enhancement strategies for different phases. On the other hand, knowledge content in online and offline phases is directly related, with online learning processes and outcomes directly influencing students' learning processes and experiences in face-to-face classes (Liu & Wang, 2021). From a process perspective, enhancing cognitive engagement in blended teaching requires optimizing the systematic learning and teaching process, seeking optimal synergistic effects across the continuous process from the pre-online self-study phase to the subsequent face-to-face classroom phase. However, previous studies have often focused on single phases of blended classrooms for educational research and practice, neglecting the essential characteristic that blended classrooms are both stage-based and process-oriented. Therefore, this study adopts a combined approach of stage-based and process-based investigation to systematically examine the empirical effects of cognitive engagement enhancement strategies based on online, offline, and integrated blended classroom processes.

Focusing on blended classrooms and guided by the ICAP framework (Interactive-Constructive-Active-Passive Framework), this study addresses student cognitive engagement quantification and enhancement through an interdisciplinary perspective integrating information technology, educational psychology empirical research, and applied research. By integrating text analysis, video analysis, eye-tracking technology, and psychometric indicators, we will establish a quantitative model of cognitive engagement, explore enhancement methods from multi-teaching-element perspectives, validate their effectiveness in real blended classrooms, and develop a teaching-research tool for dynamic identification and intervention of cognitive engagement, aiming to improve learners' cognitive engagement and learning outcomes. Through this study, we expect to provide theoretical support and specific implementation pathways for enhancing student cognitive engagement in blended classrooms.

2.1.1 Cognitive Engagement and Its Indicators in Blended Classrooms

Cognitive engagement in learning refers to learners' level of mental participation (Li et al., 2021), reflecting the degree of mental effort and cognitive strategy application when completing learning tasks (Liu et al., 2022). It is closely related to learning outcomes (Xie et al., 2020; Xu et al., 2023), and its quality and quantity can predict academic achievement (Krause & Coates, 2008). Since Professor Michelene T.H. Chi from Arizona State University proposed the ICAP framework, research focus on cognitive engagement has gradually shifted from broad conceptual exploration to fine-grained behavioral observation and quantification (Chi & Wylie, 2014). The ICAP framework proposes that learners' cognitive engagement levels can be understood through their verbal and behavioral outputs, specifically divided into four ascending levels: Passive, Active, Constructive, and Interactive. Different levels of cognitive engagement exhibit distinct behavioral patterns. Passive learning refers to students passively receiving knowledge, such as listening to peers or viewing materials. Active learning involves students actively manipulating knowledge, such as taking notes. Constructive learning refers to students developing their own understanding based on prior knowledge, such as generating their own questions. Interactive learning involves students evaluating others' understanding, such as providing critical suggestions. This theory provides example activities to promote cognitive engagement, allowing researchers and educators to infer learners' cognitive engagement levels from observable behaviors (Zhang et al., 2020).

How can we quantify cognitive engagement changes resulting from learning activities? Compared to observable behavioral engagement, cognitive engagement is more implicit, representing cognitive and psychological investment that poses greater challenges for identification. Traditional cognitive engagement assessment primarily employs self-reporting and content analysis. In self-report methods, Greene (2015) measured cognitive engagement through questionnaires and explored its relationship with learners' achievement goals. Content analysis is a commonly used technique involving systematic, objective, and quantitative description of explicit communication content (Gašević et al., 2015). Lee (2020) used automated content analysis systems to examine adolescents' cognitive engagement during English writing. Zhou and Han (2018) used content analysis based on an established cognitive engagement analysis framework to categorize cognitive engagement levels and calculate behavioral frequency metrics to infer learners' engagement. Xu et al. (2020) divided cognitive engagement into four categories—questions, statements, reflections, and scaffolding—and applied content analysis to examine students' online discussion discourse. Both traditional measurement methods have limitations, including insufficient objectivity and timeliness, making it difficult to continuously and dynamically capture developmental changes in cognitive engagement.

Multi-modal Learning Analysis represents an effective approach to exploring learning patterns. On one hand, compared to single-modal data indicators that suffer from data source limitations and low explanatory power for outcome variables like cognitive engagement, applying multi-modal data can improve the explained variance of outcome variables and provide important guidance for educational interventions. For instance, Liao and Wu (2022) collected interaction records from Facebook study groups to establish objective indicators of peer learning participation based on subjective assessments, increasing the explanatory rate for learning performance by 5%. On the other hand, multi-modal data represents information from multiple entities, including tensor or vector representations of images, audio-video, or physiological data (Zhang et al., 2022). Multi-modal data originates from different channels that may be subjective or objective. Analyzing multiple signals and their interdependencies can produce models that more accurately reflect the underlying nature of learning engagement (Sinatra et al., 2015). With advances in information and sensing technology, collecting students' multi-modal data in real classroom environments has become a trend. Portable data collection devices provide effective measurement means for multi-modal learning analysis. Lee et al. (2019) collected learners' electrodermal activity to measure cognitive engagement in maker learning activities. Baceviciute et al. (2022) incorporated eye-tracking and EEG to explore students' cognitive engagement in virtual reality learning environments. Dubovi (2022) measured cognitive and emotional engagement more objectively and comprehensively based on multi-modal data including facial expressions, eye-tracking, and electrodermal activity, and explored their impact on learning performance. However, a recent systematic literature review noted that "multimodal learning analytics research has not yet reached its potential." Due to challenges in synchronizing multi-modal data, studies using automatic continuous psychophysiological measurements are typically limited to single data streams (Sharma & Giannakos, 2020). This study aims to combine self-reporting with explicit learning behaviors and physiological measurements, focusing on textual discourse, learning behaviors, eye-tracking data, and psychometric indicators to establish a quantitative model of students' cognitive engagement in blended classrooms, providing new research insights for examining learners' internal cognitive processes during blended teaching.

Furthermore, most existing cognitive engagement research employs cross-sectional designs that collect cognitive engagement data at specific time points to describe its status, paying insufficient attention to lag effects and making it difficult to reflect dynamic change processes. Ma and Yue (2020) used the experience sampling method to collect immediate engagement data at the beginning, middle, and end of a semester in blended learning, then applied cross-lagged models to analyze longitudinal data and explain relationships between engagement at different learning stages. Although emphasizing immediacy and continuity, using experience sampling to obtain frequent self-report data from learners can lead to issues such as overly short collection periods, excessive density, and high repetition, potentially affecting response validity.

Epistemic Network Analysis quantitatively analyzes discourse data to describe individual or group cognitive framework patterns, featuring significant capabilities for analyzing multi-dimensional data, coupling relationships, deep data mining, and dynamically assessing learners' cognitive thinking development (Wu et al., 2018). Traditional learning analysis methods (e.g., content analysis, semantic analysis, machine learning) only indirectly represent learners' internal cognitive structures, tending to treat learning behaviors as isolated actions that cannot comprehensively and dynamically present characteristics and changes in learners' cognitive network structures (Wang & Yang, 2019). Epistemic network analysis can utilize sequential data presented during learning processes to establish association structures of co-evolution among students' cognitive elements, reflecting dynamic changes in learners' cognitive structures at a deeper level.

Students' knowledge develops dynamically through practice, posing a challenge for when and how teachers should adopt instructional strategies to effectively guide learning. To evaluate whether teaching strategies are effective, researchers typically compare learning outcomes before and after teaching activities. However, this method cannot effectively reflect how teaching strategies guide students to develop their own cognition. Only by fundamentally understanding the essence of teaching strategies (i.e., the cognitive change patterns of teachers and students during strategy use) can we provide support for subsequent strategy development. Therefore, we can apply epistemic network analysis to teacher and student discourse data, evaluating teaching strategy effectiveness by exploring changes in students' cognitive networks during class.

In summary, quantification of learners' cognitive engagement has gradually evolved from subjective assessment to objective indicators, establishing evaluation index systems from multiple perspectives. However, issues remain regarding single modality, lack of dynamic analysis, and teaching context limitations. This study aims to integrate multi-modal data including textual discourse, eye-tracking, learning behaviors, and psychometric indicators to establish a quantitative model of learners' cognitive engagement, providing substantive evidence of how teaching strategies cause changes in cognitive engagement. Additionally, in real teaching tracking studies, we will combine dynamic epistemic network analysis to examine the co-evolution of teacher strategies and student group cognitive structures, providing multi-dimensional evidence for cognitive engagement changes.

2.1.2 Factors Influencing Student Cognitive Engagement in Blended Classrooms

Appropriate use of cognitive strategies can promote better learning engagement (Anthonysamy et al., 2020). The blended teaching model integrates stage-based and process-based characteristics, featuring complex elements and diverse learning contexts (Tian et al., 2019). The rational design of teaching organization methods and the integration and penetration of online self-study and offline teaching to promote student cognitive engagement are major concerns for blended classroom education researchers and practitioners (Wen & Mu, 2023).

In the online self-study phase, students master foundational knowledge through interaction with instructional content, where instructional resource design and student learning strategies are key factors affecting online learning processes and outcomes. Designing appropriate content presentation methods helps enhance cognitive engagement. Instructional videos featuring instructor-generated drawings have emerged as a prominent approach. Instructor-Generated Drawings are instructional videos that simultaneously present manually drawn content (e.g., charts, flowcharts) with oral explanations, attracting student attention through continuous drawing, integrating visual images with instructor speech, and providing social cues through the instructor's speech and gestures during drawing. Instructor gestures, as an important component of instructor image design, affect learners' cognitive engagement and learning outcomes (Pi et al., 2019; Tian et al., 2021). Instructor gestures not only supplement semantic information in speech but also guide learners' attention allocation and elicit positive social responses, influencing cognitive processes and affecting learning outcomes.

Combining instructor gestures with appropriate content presentation methods can effectively promote learning effectiveness. Under dynamic presentation conditions, instructor presence and gesture guidance appear particularly beneficial, as gesture-expressed information and dynamically presented content form coherent information that helps learners understand logical relationships between knowledge points and construct systematic knowledge structures.

Generative Learning Strategies refer to strategies that guide learners to initiate appropriate cognitive processing (e.g., information selection, organization, and integration) during learning to facilitate generative learning (Yang et al., 2021; Fiorella & Mayer, 2015). For example, the Learning by Self-explaining strategy emphasizes learners generating self-explanations combining learned knowledge, including oral or written explanations. The question-generation strategy requires learners to process knowledge by generating questions about learning content and providing answers, which can be done individually or with peers (Yu & Kuo, 2024). "Self-explaining" and "question-generation" are effective generative learning strategies based on knowledge summarization and comprehension. As the ancient saying goes, "Learning without thinking leads to confusion; thinking without learning leads to danger" (The Analects, Wei Zheng), the combined use of "summarization" and "thinking" generative learning strategies requires further investigation for its promoting effect on learning outcomes.

A key aspect of blended teaching is the organic integration of pre-class learning with face-to-face teaching activities (Qian & Chen, 2015; Tian & Xi, 2020). Educators should focus on learners' needs and deeply engage in blended classroom teaching and learning strategy design (Wen & Mu, 2023). Organically combining students' question generation during online autonomous learning with teachers' guidance during instruction is a critical pathway to enhancing blended classroom effectiveness. Some blended teaching approaches focus on addressing students' pre-class questions during face-to-face instruction. Students' questions externally manifest as learning confusion but internally represent elaboration and metacognitive processes of learning content. Teachers can thereby identify "gaps" between students' prior knowledge and course content, including understanding, organization, expression, and meaning construction. Student questions serve as the basis for "teaching based on learning," requiring integration of online question generation with offline teaching (Cao & Ma, 2020). Teachers' effective questions can guide and promote learners' deep thinking and interaction with learning content. Question scaffolding refers to question sets that provide learning support from cognitive and metacognitive levels to guide and facilitate learning (Ge & Er, 2005), decomposing course content based on knowledge points and stimulating thinking and communication through question-and-answer formats (Hao et al., 2019). When teachers ask questions based on students' online questions, different question scaffolding approaches may yield different teaching effects, with reflective teaching methods (e.g., guiding students to analyze their own problem-solving processes) being more effective for stimulating deep thinking.

Teaching Feedback refers to information provided to learners about task completion status, helping them understand and narrow the gap between current and target learning states (Hattie & Timperley, 2007), and constitutes a learning-promoting activity. Based on complexity, feedback can be categorized as simple or elaborated (Shute, 2008). Simple feedback confirms whether learners' answers are correct, while elaborated feedback explains reasons for correctness beyond providing accuracy information. Based on explanation content differences, feedback can be further divided into types including directive and descriptive feedback. Descriptive feedback provides objective descriptions of learning status without any comments or suggestions, while directive feedback is more systematic and planned, providing detailed explanations of problems and their causes, adding systematic guidance for problem-solving (Li et al., 2013). Feedback complexity affects learning outcomes, with more elaborated feedback better promoting learners' self-efficacy, motivation, and academic performance during learning (Wang & Wu, 2008).

The effectiveness of teachers' feedback types on learning outcomes is moderated by learners' characteristics (Wu & Peng, 2021). For example, feedback has greater promoting effects on learners with lower prior knowledge compared to those with higher prior knowledge (Fyfe et al., 2012). In blended teaching modes, learners with different cognitive levels master different content through autonomous online resource learning, with higher-level learners possessing richer prior knowledge through online learning. Therefore, in blended contexts, the promoting effect of teachers' feedback types on learning outcomes may differ based on learners' cognitive levels.

Emotional information in feedback can help learners improve emotional self-awareness and regulate emotions in a timely manner (Wang et al., 2021a). Research shows that specific feedback design can elicit positive emotions and increase cognitive engagement by increasing relevant cognitive load (Wang et al., 2021b), with positive feedback methods more effectively improving cognitive engagement. Existing research mostly examines the combination of feedback types and emotional design in video learning, with the generalizability of findings to blended teaching contexts requiring further investigation.

Reflection, as a key component at the end of the learning process, is also an important factor affecting learning outcomes (Shen et al., 2022). In blended teaching with diverse learning environments, learners' reflection on the entire learning process enables detailed understanding and holistic grasp of learning content. Reflection logs and mind maps are typical post-class reflection forms. Writing reflection logs involves learners re-examining the entire learning process from a critical perspective through written text after class (Bu et al., 2022), helping them review learning processes, evaluate outcomes, identify deficiencies, and adjust learning status to further improve reflection levels and metacognitive abilities (Yang et al., 2011). Mind maps are visual thinking tools that promote learners' memory, creativity, and thinking about learning content, facilitating holistic understanding (Zhao et al., 2019). Few studies have compared the relative effectiveness of these two reflection forms. The reflection subject also affects effectiveness, with group learning being a common organization form in blended teaching. Individual reflection is less comprehensive than group collaborative reflection. Mind map reflection can concisely and quickly provide holistic information about learning content, while reflection logs focus more on details with complex presentation formats that hinder perception of group reflection outcomes. In collaborative settings, mind map reflection may be more effective for improving learning outcomes.

In summary, to achieve the integration of online and offline education in blended teaching, this study adopts stage-based and process-based perspectives to explore blended teaching cognitive engagement enhancement strategies from the perspective of important influencing factors, forming an intervention strategy set for digital teaching tools.

2.2 Significance of This Study

Theoretically, this study establishes a quantitative model of cognitive engagement by integrating multi-modal indicators, providing a basis for measuring student cognitive engagement in blended classrooms and offering associated indicators for future research on the neural mechanisms underlying how teaching activities affect cognitive engagement. Practically, this study will propose blended teaching solutions aimed at enhancing student cognitive engagement and develop a digital auxiliary tool for cognitive engagement identification and intervention in blended classrooms, contributing to advancing AI integration throughout the teaching process and improving teachers' digital literacy.

3 Research Framework

Previous research has identified student cognitive engagement level as a key factor affecting learning outcomes. However, given its deep implicit nature, accurate representation and scientific quantification of cognitive engagement through interdisciplinary perspectives, multi-modal data, and information technology constitute an effective measurement approach and important prerequisite for improving blended teaching effectiveness. Blended classrooms feature multi-stage, cross-context learning characteristics, where digital learning implies that collecting learning process data through information science technology is essential for understanding student cognitive engagement. Therefore, this study aims to achieve theoretical and practical goals by leveraging advantages in information science and educational psychology to establish multi-modal cognitive engagement indicators, examine enhancement strategy effectiveness through laboratory experiments and teaching tracking, and develop teaching tools to provide theoretical and instrumental support for improving student cognitive engagement in blended classrooms.

This study comprises four research components. Study 1 establishes multi-modal cognitive engagement indicators and a quantitative model for blended classrooms guided by the ICAP framework, obtaining multi-modal data through text analysis, video analysis, eye-tracking, and psychometric measurement. Study 2 explores cognitive engagement enhancement strategies and their mechanisms through behavioral, eye-tracking, and functional near-infrared spectroscopy experiments in educational psychology. Study 3 validates enhancement strategy effectiveness in real blended classrooms through a semester-long tracking study integrating multi-modal indicators and epistemic network analysis to examine ecological validity. Study 4 uses neural network algorithms to build classifiers, forming an intelligent identification and intervention teaching-research tool for cognitive engagement in blended classrooms that monitors student engagement states in real-time and provides teachers with timely instructional strategy guidance. The research framework is shown in Figure 1 [Figure 1: see original paper].

3.1 Study 1: Multi-modal Data-Based Cognitive Engagement Quantification Model Construction

Multi-modal data will be collected from different learning stages and time scales in real blended classrooms (including 6 natural classes with 300 students). The online component focuses on students' online behaviors (e.g., video clicks, posts, replies) and discussion forum text, while the offline component focuses on students' verbal and non-verbal data in face-to-face classes. Based on video, textual discourse, eye-tracking, and other multi-modal channels, we will establish a quantitative model of learners' cognitive engagement, examining engagement at both class-wide and individual student levels. As shown in Figure 2 [Figure 2: see original paper], multi-modal data in blended classrooms mainly includes textual discourse data, video data, online learning data, physiological (eye-tracking) data, etc.

Modality 1: Textual Discourse Data. Python will be used to crawl learners' online discussion and comment texts from learning platforms, and audio recordings of students' answers or discussions in face-to-face classes will be transcribed. In text analysis, researchers typically use psychological dictionaries and text analysis tools such as LIWC and Coh-Metrix to extract textual discourse features of individuals at different cognitive engagement levels.

Modality 2: Video Data. Behavioral data coding will be conducted using classroom observation or video recording. Building upon FIAS interaction analysis coding and Gu Xiaoqing's ITIAS, this study extracts feature indicators more aligned with university learners' cognitive behaviors to explore behavioral characteristics of individuals engaged in different cognitive activity types.

Modality 3: Online Learning Data. Data obtained from online system log files will be used to create online behavioral datasets, such as learning duration, posting/replying, fast-forwarding/pausing, enabling indirect measurement of cognitive engagement.

Modality 4: Eye-tracking Data. Learners will wear portable Tobii Pro eye-trackers during both online and offline learning phases. Based on previous research on eye-tracking indicators and cognitive engagement, this study selects three types of eye-tracking indicators (fixation, saccade, and pupil diameter) as the foundation for building the quantitative model.

Modality 5: Psychometric Data. The Online Learning and Classroom Learning Cognitive Engagement Questionnaire (Liu & Wang, 2021) will be administered for learners' self-reporting.

Additionally, social network analysis (absolute out-degree, absolute in-degree, and degree centrality) will be used to calculate interaction relationships in textual and behavioral data, obtaining social interaction-level data that reflects learners' interaction levels with teachers and peers and cognitive engagement at the interaction level.

Cognitive engagement quantification dimensions include behavioral participation, cognitive construction, and social interaction. Specific indicators and measurement methods are shown in Table 1 .

A combined subjective-objective method will be used to establish relationships between cognitive engagement and various indicators, obtaining optimal weight coefficients for cognitive engagement measurement. Model construction comprises two stages: indicator collection and model calculation. The indicator collection stage implements multi-modal data collection and cleaning, while the model calculation stage primarily uses entropy methods and grey relational analysis to construct functional mapping relationships between indicators and cognitive engagement scale measurements.

3.2 Study 2: Laboratory Investigation of Cognitive Engagement Enhancement Strategies

In the blended teaching context, laboratory experiments will be conducted from stage-based and process-based perspectives, focusing on two main pathways: instructional resource optimization and teaching strategy refinement. Specifically, Study 2 includes 3 sub-studies with 6 laboratory experiments:

Sub-study 1 focuses on the online phase of blended teaching, examining the effects of instructional resources and learner-generated strategies. Experiment 1 uses eye-tracking technology to investigate how video content presentation methods and instructor gesture guidance affect cognitive engagement, employing a 3 (content presentation: instructor-generated drawings, animation, no animation) × 3 (gesture guidance: with gestures, without gestures, no instructor) between-subjects design (Figure 3 [Figure 3: see original paper]). Experiment 2 examines how generative learning strategies (self-explaining, question-generation) promote cognitive engagement, using a 2 (self-explaining: yes, no) × 2 (question-generation: yes, no) between-subjects design. Dependent variables include cognitive engagement (represented by multi-modal data), learning outcomes (retention and transfer test scores), and subjective learning experience (motivation, self-efficacy, extraneous cognitive load, perceived task difficulty, mental effort). These measures are divided into online learning indicators and overall blended classroom indicators.

Sub-study 2 adopts a process-based perspective on the internal connection between online self-study and offline learning phases, combining functional near-infrared spectroscopy to explore how different teaching strategies promote cognitive engagement and reveal underlying neurocognitive mechanisms. Experiment 3 investigates the effects of learners' online question-generation strategies and teachers' offline question-scaffolding strategies on cognitive engagement during the face-to-face phase, using a 2 (student question-generation: yes, no) × 3 (teacher question-scaffolding: descriptive, reflective, none) between-subjects design. Experiment 4 examines how learners' cognitive levels and teachers' offline feedback strategies affect cognitive engagement, using a 2 (cognitive level: lower-order, higher-order) × 2 (teacher feedback: directive, descriptive) between-subjects design. Dependent variables build upon Sub-study 1 with the addition of Interpersonal Neural Synchronization (INS) as a physiological indicator.

Sub-study 3 focuses on the offline face-to-face classroom phase, sequentially investigating how teachers' different instructional strategies during and after class affect cognitive engagement. Experiment 5 examines how teachers' in-class feedback strategies (feedback type, feedback valence) affect cognitive engagement, using a 2 (feedback strategy: directive, descriptive) × 2 (emotional valence: positive, neutral) between-subjects design. Experiment 6 investigates how teachers' post-class reflection strategies (reflection form, reflection subject) promote cognitive engagement, using a 2 (reflection form: mind map, reflection log) × 2 (reflection subject: individual, group) between-subjects design. Dependent variables include cognitive engagement, learning outcomes, and subjective learning experience.

Based on discussions of cognitive engagement enhancement strategies throughout the entire blended teaching process, Study 2 will establish an effective strategy set and provide theoretical support for subsequent teaching tracking and tool development.

3.3 Study 3: Validation of Enhancement Strategy Effectiveness in Real Classroom Environments

From a dynamic development perspective, this study conducts a one-semester tracking study in real blended classrooms. Based on the superior teaching strategies validated in Study 2, instructional programs will be developed and validated through teaching practice to examine their effects on student cognitive engagement and learning performance. Using convenience sampling, two non-psychology major natural classes from a normal university will be selected, with the principle that both classes have a one-semester psychology course arrangement ("Public Foundation Psychology Course") taught by the same instructor. This experiment employs a single-factor (blended teaching mode: experimental group, control group) between-subjects design (Figure 4 [Figure 4: see original paper]). This study further examines class-level cognitive engagement in blended classrooms, combining epistemic network analysis to investigate differences in cognitive engagement levels and cognitive structures between experimental and control groups. Meanwhile, longitudinal cognitive network models will be constructed to examine the dynamic evolution of experimental group students' cognitive structures over time as the instructional program is implemented.

3.4 Study 4: Development and Effectiveness Validation of a Teaching-Research Auxiliary Tool for Cognitive Engagement in Blended Classrooms

Aiming to improve ecological validity and innovate educational practice applications, this study will construct an automatic identification model for student cognitive engagement in blended classrooms, integrating multi-modal measurement indicators (text, action, physiology, psychology). Using Spring Cloud backend framework, Vue with Element components frontend framework, and MySQL database, a digital auxiliary tool integrating cognitive engagement identification and intervention functions will be established. Real teaching practice and controlled studies will be implemented to test the tool's promoting effects on learners' cognitive engagement and learning outcomes in blended classrooms.

3.4.1 Construction of a Classification Model for Student Cognitive Engagement in Blended Classrooms

Using multi-modal indicators from Study 1 as input features, feature selection will be applied to identify important features, and deep neural network algorithms will be used to build a cognitive engagement classification model for intelligent identification.

(1) Data Collection and Preprocessing. Data sources include the online and offline process learning data of 300 students collected in Study 1. Each sample contains online learning system data, video data, eye-tracking data, and textual discourse data. The collected multi-modal data will be inspected and filtered, removing samples with collection errors or missing data.

(2) Multi-modal Feature Extraction. The dataset includes feature and label data. Feature data originates from multi-modal data analysis. Video data uses 10-second segments of classroom recordings as analysis units, coding students' behavioral actions in each unit to obtain feature vectors including gaze direction, head pose, and gestures. Eye-tracking data is preprocessed using Tobii Studio software to export temporally and spatially tracked data and extract eye-tracking features. Regarding textual discourse data, since text is unstructured and cannot be directly processed by computers, vectorization is required. A psychological dictionary-based method will extract text features, representing each student's complete text as a series of word frequency features.

Based on collected explicit behavioral data and the ICAP framework, associated cognitive engagement states (passive, active, constructive, interactive) will be determined, and explicit behaviors will be labeled accordingly (Table 2).

(3) Feature Selection. Multiple feature selection methods including variance selection, chi-square tests, and Recursive Feature Elimination (RFE) will be used to identify the most important cognitive engagement evaluation features (further screening based on extracted indicators to avoid overfitting).

(4) Model Training and Evaluation. This study will use a neural network model combining LSTM and CNN to construct sequential models for learning behaviors and eye-tracking trajectories. Using eye-tracking data as an example, the CNN component uses 1 convolutional layer and 1 pooling layer, with 2 convolutional kernels of size 4$×4andstride1,andapoolinglayerofsize2×$2 with stride 2. In the LSTM component, the number of hidden neurons equals the input eye-tracking data length of 50. Left and right eye inter-frame difference videos will be input simultaneously. After convolutional layers, feature maps extracted from both eye videos will be merged through a channel concatenation layer, with feature dimensions forming a cube that is vectorized through a flattening layer and input into LSTM. Finally, a fully connected layer calculates probabilities for each eye-tracking behavior. Pre-trained models will use 10-fold cross-validation to select optimal hyperparameter combinations as algorithm parameters, determining the best feature selection and classification model. Accuracy, recall, and F1-score will serve as evaluation metrics.

3.4.2 Development of an Intelligent Identification and Intervention Teaching-Research Auxiliary Tool for Cognitive Engagement

The overall architecture will be designed based on Service-Oriented Architecture (SOA) concepts, as shown in Figure 5 [Figure 5: see original paper].

The tool comprises six modules: classification model training, classroom data collection, cognitive engagement identification, data display, intervention strategy triggering, and teaching strategy push. (1) The model training module uses Study 1 data to train the cognitive engagement identification and classification model for subsequent modules. (2) The classroom data collection module implements data collection in blended classrooms, including online learning system data, video data, eye-tracking data, and textual discourse data. Collected data will be labeled with identity using trained identification models and standardized for storage. (3) The cognitive engagement identification module imports classroom data into the CNN-LSTM model for identification and classification, saving obtained categories and overall class cognitive engagement status. (4) The data display module statistically analyzes identification results to generate classroom reports for teachers, supporting instructional strategy improvement. (5) Intervention strategy triggering mechanism (Figure 6 [Figure 6: see original paper]). (6) Teaching strategy push module (Figure 7 [Figure 7: see original paper]). Based on student cognitive engagement states, intervention strategies will be triggered and subsequent behaviors observed. Through multiple empirical experiments, intervention model parameters will be iteratively updated, adjusted, and refined.

4 Theoretical Construction and Innovation

As an important teaching model in educational digital transformation, blended classrooms differ from traditional classrooms primarily in their integration of both stage-based teaching formats and process-based cognitive development. In this complex teaching process, cognitive engagement's implicit nature increases measurement and intervention difficulty. Guided by the ICAP framework and relying on interdisciplinary research, this study addresses the core issue of "quantification and intervention of student cognitive engagement in blended classrooms."

(1) **Proposing a multi-modal data-based cognitive engagement model to establish a quantitative representation system.** Addressing the implicit nature of cognitive engagement, this study integrates three feature dimensions—behavior, cognition, and social interaction—to obtain multi-modal data including text, behavior, eye-tracking, and psychometric measurements, establishing a cognitive engagement quantification model for the entire blended classroom process.

(2) **Adopting stage-based and process-based research perspectives to explore blended classroom teaching strategy optimization.** Using a two-phase blended classroom experimental paradigm, this study reproduces and simulates blended teaching processes in laboratory settings, combining eye-tracking and functional near-infrared spectroscopy to explore internal mechanisms and ideal expected effects of teaching strategies on cognitive engagement, providing "gold standard" evidence from evidence-based research.

(3) **Aiming to improve ecological validity and innovate educational practice, proposing a higher education blended teaching solution and developing an integrated teaching-research auxiliary tool.** Using Spring Boot2, Spring Cloud Hoxton, Mybatis and other technologies, an intelligent identification and intervention tool for cognitive engagement in blended classrooms will be designed and built. The tool is expected to provide teachers with auxiliary support for blended classrooms, enabling intelligent identification and analysis of learners' cognitive engagement levels to form individual and class-wide engagement data, providing real-time feedback and teaching strategy recommendations.

References

Bu, C., Li, S., Wang, J., Zhang, S., & Dong, L. (2022). Thinking for deep learning: An empirical study on how reflection logs promote college students' metacognitive development. *Modern Educational Technology*, 32(9), 73−81.

Cao, M., & Ma, Y. (2020). Research on question generation strategies for deep learning in pre-class flipped classroom. *e-Education Research*, 41(11), 101−107.

Hao, X., Wang, F., & Wang, Y. (2019). Hypothesis and verification of the pathway for question scaffolding to promote online knowledge interaction. *Chinese Journal of Distance Education*, 3, 34−42+92−93.

Jiang, Q., Pan, X., Zhao, W., & Liu, H. (2018). Research on the influence of teachers' motivational styles on learning engagement in online learning spaces—The mediating effect of intrinsic motivation in SDT. *China Educational Technology*, 380, 7−16.

Li, K., & Zhao, J. (2004). Principles and application models of blended learning. *e-Education Research*, 135, 1−6.

Li, L., Xu, R., & Zheng, Y. (2013). Design of online learning feedback from the perspective of the ARCS model. *Modern Distance Education*, 147, 66−71.

Liu, L., & Wang, Q. (2021). Research on the characteristics and influencing factors of student learning engagement in blended teaching mode. *Modern Educational Technology*, 31(11), 80−86.

Lu, G., Liu, Q., Zheng, Q., & Xie, K. (2021). Research on the influence of environmental perception and self-efficacy on individual cognitive engagement in smart classrooms. *Journal of Distance Education*, 39(3), 84−93.

Ma, Z., & Yue, Y. (2020). A longitudinal study of learning engagement for real-time data collection and analysis—A comprehensive application based on experience sampling method and cross-lagged analysis. *e-Education Research*, 41(4), 71−77.

Pi, Z., Zhang, Y., & Yang, J. (2019). The influence of teacher gestures on video learning and its cognitive neural mechanism. *China Educational Technology*, 387, 103−110+129.

Qian, Y., & Chen, X. (2015). Design principles of flipped classroom at the University of Southern California and their implications. *China Educational Technology*, 341, 99−103.

Shen, X., Zhang, B., & Feng, R. (2022). Research on deep learning activities in blended learning environments: A triad of design, implementation, and evaluation. *e-Education Research*, 43(1), 106−112.

Shi, Y., Tong, M., Wang, J., Sun, J., Dai, H., & Wei, Y. (2021). Blended synchronous learning: Evolution, value, and future issues. *e-Education Research*, 42(12), 100−107.

Tian, H., & Wu, F. (2022). Research on multimodal representation and analysis path of collaborative cognitive engagement in blended scenarios. *Journal of Distance Education*, 40(4), 35−44.

Tian, Y., Chen, P., Huang, R., & Zeng, H. (2019). Multimodal interaction analysis mechanism and optimization strategies for blended learning. *e-Education Research*, 40(9), 67−74.

Tian, Y., Qi, Z., Huang, X., Xiang, H., & Wang, Y. (2021). The cognitive neural mechanism of social cues promoting online learning. *e-Education Research*, 42(2), 63−69.

Tian, Y., & Xi, Y. (2020). Applied research on blended classroom teaching models in higher education. *China University Teaching*, 8, 78−86.

Wang, X., Gao, Z., Xu, W., & Zhang, L. (2021a). Research on the influence mechanism of emotional design of feedback on video learning. *e-Education Research*, 42(3), 69−74.

Wang, X., Zhang, L., Yang, W., Lu, X., Xu, W., & Gao, Z. (2021b). How online learning resources affect academic emotions and learning outcomes—A meta-analysis based on control-value theory. *Modern Distance Education Research*, 33(5), 82−93+102.

Wang, Z., & Yang, Y. (2019). Cognitive network analysis method and its application case analysis. *e-Education Research*, 40(6), 27−34.

Wen, H., & Mu, S. (2023). How can different paths lead to the same destination?—Analysis of the effects of blended teaching practices with different complexity levels. *Chinese Journal of Distance Education*, 43(2), 64−72.

Wu, S., & Peng, Z. (2021). Towards more effective feedback: Hattie's model of "Visible Learning". *Open Education Research*, 27(4), 27−40.

Wu, B., Wang, G., & Sheng, H. (2018). Cognitive network analysis: A new approach to learning assessment in STEM education. *Journal of Distance Education*, 36(6), 3−10.

Yang, J., Zhang, R., Jiang, L., & Huang, L. (2011). Strategies and research on improving normal university students' reflective ability based on blogs. *China Educational Technology*, 298, 62−66.

Yang, J., Zhang, Y., Xu, K., & Pi, Z. (2021). The influence of learning strategies on video learning: Imagining, drawing, and self-explaining strategies. *e-Education Research*, 42(10), 40−47.

Zhang, L., Du, X., Li, H., Xie, Y., & Tang, Y. (2022). Analysis of learning engagement assessment methods based on multimodal data. *e-Education Research*, 43(10), 72−78.

Zhang, S., He, J., Shang, C., Xia, D., & Hu, Q. (2020). A cognitive engagement analysis model for collaborative knowledge construction in online learning and its application. *Journal of Distance Education*, 38(4), 95−104.

Zhao, G., Yang, X., & Xiong, Y. (2019). On the principles and focus points of teaching application of thinking visualization tools. *e-Education Research*, 40(9), 59—66+82.

Zhou, Y., & Han, Y. (2018). Research on learners' learning engagement in blended learning activities. *e-Education Research*, 39(11), 99—105.

Anthonysamy, L., Koo, A. C., & Hew, S. H. (2020). Self-regulated learning strategies and non-academic outcomes in higher education blended learning environments: A one decade review. *Education and Information Technologies*, 25, 3677—3704. https://doi.org/10.1007/s10639-020-10134-2

Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the student engagement instrument. *Journal of School Psychology*, 44(5), 427—445. https://doi.org/10.1016/j.jsp.2006.04.002

Baceviciute, S., Lucas, G., Terkildsen, T., & Makransky, G. (2022). Investigating the redundancy principle in immersive virtual reality environments: An eye-tracking and EEG study. *Journal of Computer Assisted Learning*, 38(1), 120—136. https://doi.org/10.1111/jcal.12595

Bredow, C. A., Roehling, P. V., Knorp, A. J., & Sweet, A. M. (2021). To flip or not to flip? A meta-analysis of the efficacy of flipped learning in higher education. *Review of Educational Research*, 91(6), 878—918. https://doi.org/10.3102/00346543211019122

Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, 49(4), 219—243. https://doi.org/10.1080/00461520.2014.965823

Dubovi, I. (2022). Cognitive and emotional engagement while learning with VR: The perspective of multimodal methodology. *Computers & Education*, 183, Article 104495. https://doi.org/10.1016/j.compedu.2022.104495

Fiorella, L., & Mayer, R. E. (2015). *Learning as a generative activity: Eight learning strategies that promote understanding*. Cambridge University Press. https://doi.org/10.1017/CBO9781107707085

Fyfe, E. R., Rittle-Johnson, B., & DeCaro, M. S. (2012). The effects of feedback during exploratory mathematics problem solving: Prior knowledge matters. *Journal of Educational Psychology*, 104(4), 1094—1108. https://doi.org/10.1037/a0028389

Garrison, D. R., & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *The Internet and Higher Education*, 7(2), 95—105. https://doi.org/10.1016/j.iheduc.2004.02.001

Gašević, D., Adesope, O., Joksimović, S., & Kovanović, V. (2015). Externally-facilitated regulation scaffolding and role assignment to develop cognitive presence in asynchronous online discussions. *The Internet and Higher Education*, 24, 53–65. https://doi.org/10.1016/j.iheduc.2014.09.006

Ge, X., & Er, N. (2005). An online support system to scaffold real-world problem solving. *Interactive Learning Environments*, 13(3), 139–157. https://doi.org/10.1080/10494820500382893

Greene, B. A. (2015). Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. *Educational Psychologist*, 50(1), 14–30. https://doi.org/10.1080/00461520.2014.989230

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1), 81–112. https://doi.org/10.3102/003465430298487

Jusoff, K., & Khodabandelou, R. (2009). Preliminary study on the role of social presence in blended learning environment in higher education. *International Education Studies*, 2(4), 79–83. https://doi.org/10.5539/ies.v2n4p79

Krause, K. L., & Coates, H. (2008). Students' engagement in first-year university. *Assessment & Evaluation in Higher Education*, 33(5), 493–505. https://doi.org/10.1080/02602930701698892

Lee, C. (2020). A study of adolescent English learners' cognitive engagement in writing while using an automated content feedback system. *Computer Assisted Language Learning*, 33(1–2), 26–57. https://doi.org/10.1080/09588221.2018.1544152

Lee, V. R., Fischback, L., & Cain, R. (2019). A wearables-based approach to detect and identify momentary engagement in afterschool Makerspace programs. *Contemporary Educational Psychology*, 59, Article 101789. https://doi.org/10.1016/j.cedpsych.2019.101789

Li, S., Lajoie, S. P., Zheng, J., Wu, H., & Cheng, H. (2021). Automated detection of cognitive engagement to inform the art of staying engaged in problem-solving. *Computers & Education*, 163, Article 104114. https://doi.org/10.1016/j.compedu.2020.104114

Liao, C. H., & Wu, J. Y. (2022). Deploying multimodal learning analytics models to explore the impact of digital distraction and peer learning on student performance. *Computers & Education*, 190, Article 104599. https://doi.org/10.1016/j.compedu.2022.104599

Lightner, C. A., & Lightner-Laws, C. A. (2016). A blended model: Simultaneously teaching a quantitative course traditionally, online, remotely. *Interactive Learning Environments*, 24(1), 224–238. https://doi.org/10.1080/10494820.2013.841262

Liu, S., Liu, S., Liu, Z., Peng, X., & Yang, Z. (2022). Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement. *Computers & Education*, 181, Article 104461. https://doi.org/10.1016/j.compedu.2022.104461

Miller, B. W. (2015). Using reading times and eye-movements to measure cognitive engagement. *Educational Psychologist*, 50(1), 31–42. https://doi.org/10.1080/00461520.2015.1004068

Müller, C., & Mildenberger, T. (2021). Facilitating flexible learning by replacing classroom time with an online learning environment: A systematic review of blended learning in higher education. *Educational Research Review*, 34, Article 100394. https://doi.org/10.1016/j.edurev.2021.100394

Porter, W. W., Graham, C. R., Spring, K. A., & Welch, K. R. (2014). Blended learning in higher education: Institutional adoption and implementation. *Computers & Education*, 75, 185—195. https://doi.org/10.1016/j.compedu.2014.02.011

Rotgans, J. I., & Schmidt, H. G. (2011). Cognitive engagement in the problem-based learning classroom. *Advances in Health Sciences Education*, 16(4), 465—479. https://doi.org/10.1007/s10459-011-9272-9

Sharma, K., & Giannakos, M. (2020). Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology*, 51(5), 1450—1484. https://doi.org/10.1111/bjet.12993

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research*, 78(1), 153—189. https://doi.org/10.3102/0034654307313795

Sinatra, G. M., Heddy, B. C., & Lombardi, D. (2015). The challenges of defining and measuring student engagement in science. *Educational Psychologist*, 50(1), 1—13. https://doi.org/10.1080/00461520.2014.1002924

Walker, C. O., Greene, B. A., & Mansell, R. A. (2006). Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement. *Learning and Individual Differences*, 16(1), 1—12. https://doi.org/10.1016/j.lindif.2005.06.004

Wang, S. L., & Wu, P. Y. (2008). The role of feedback and self-efficacy on web-based learning: The social cognitive perspective. *Computers & Education*, 51(4), 1589—1598. https://doi.org/10.1016/j.compedu.2008.03.004

Xie, K., Vongkulluksn, V. W., Lu, L., & Cheng, S. L. (2020). A person-centered approach to examining high-school students' motivation, engagement and academic performance. *Contemporary Educational Psychology*, 62, Article 101877. https://doi.org/10.1016/j.cedpsych.2020.101877

Xu, B., Chen, N. S., & Chen, G. (2020). Effects of teacher role on student engagement in WeChat-Based online discussion learning. *Computers & Education*, 157, Article 103956. https://doi.org/10.1016/j.compedu.2020.103956

Xu, X., Shi, Z., Bos, N. A., & Wu, H. (2023). Student engagement and learning outcomes: An empirical study applying four-dimensional framework. *Medical Education Online*, 28(1), Article 2268347. https://doi.org/10.1080/10872981.2023.2268347

Yu, F. Y., & Kuo, C. W. (2024). A systematic review of published student question-generation systems: Supporting functionalities and design features. *Journal of Research on Technology in Education*, 56(2), 172—195. https://doi.org/10.1080/15391523.2022.2119448

Note: Figure translations are in progress. See original paper for figures.