Research on the Innovation of Blended Course Construction Models Based on AIGC

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Abstract: *Generative artificial intelligence is transforming the way educational content is organized, and traditional blended courses find it difficult to adapt to its dynamism in terms of preset modules, linear interactions, and static evaluations. This study focuses on the innovation of AIGC-based blended course construction models and builds a framework from three levels: identifying the bottlenecks of traditional architectures, redefining course elements, and designing a three-layer human-machine collaborative structure; establishing a dynamic construction method for knowledge units driven by multimodal semantics, and achieving adaptive path orchestration with real-time feedback and generative models; promoting the shift of evaluation from outcome measurement to process tracking, integrating multiple data with AIGC, and constructing streaming analysis and double-loop closed-loop adjustment strategies. This model provides theoretical and technical pathways for the adaptive reconstruction of blended courses.*

Keywords: *generative artificial intelligence; blended courses; human-machine collaboration; adaptive learning paths; process evaluation*

Introduction

Blended courses have long relied on preset knowledge modules and fixed interaction processes, with teachers holding relatively concentrated control over content generation and learning paths. The intervention of AIGC enables course content to be generated and adjusted in real time during the teaching process, and the dialogic interaction between learners and intelligent systems breaks the traditional linear learning rhythm. This change brings challenges on two levels: first, the existing course architecture can hardly accommodate the variability of generative content and the need for non - linear dialogue, and the online - offline integration lacks buffering mechanisms; second, the evaluation system still focuses on final outputs and fails to capture learners' behavioral traces and strategic characteristics in human- machine collaboration. Therefore, it is necessary to systematically innovate the construction model of blended courses, so that it can effectively integrate the generative capabilities of AIGC while maintaining the guidance of course objectives and the accuracy of evaluation. The significance of this study lies in redefining course elements at the theoretical level, designing content generation and path adaptation mechanisms at the technical level, and constructing process tracking and dynamic calibration systems at the evaluation level, thereby providing a complete model framework for the transformation of blended courses in the AIGC era.

1. Theoretical Foundations and Structural Reorganization of AIGC Integration into Blended Courses

1.1 Adaptive Bottlenecks of Traditional Blended Course Architectures in Generative Environments

1.1.1 Temporal Conflicts between Preset Modules and Generated Content

Once online resources are created as static texts or videos, they can hardly be synchronously integrated with the information generated by AIGC in real time. If learners initiate generative follow-up questions while viewing preset materials, the answers provided by AIGC may exceed the knowledge boundaries of the current module, thereby disrupting the learning pace. The preset exercises within the module can also hardly cover the new knowledge points elicited by the generated content, forcing learners to switch repeatedly between different systems and consequently increasing their cognitive load.

1.1.2 Constraints of Linear Interaction Paths on Dynamic Demands

The interaction paths in traditional blended courses are typically linear, requiring learners to click through courseware, answer questions, and submit in a fixed sequence. The non- linear dialogue mode supported by AIGC allows learners to jump between topics or ask follow- up questions at any time, but if the course system still adopts a fixed menu- based navigation, friction arises between the two. Learners are often forced to return to the breakpoint of the original path after the generative dialogue ends, and their original learning rhythm and attention allocation are frequently interrupted.

1.1.3 Lack of Buffering Mechanism for Online-Offline Integration

In the offline session, if teachers use AIGC to generate discussion materials, the pre- set question sets may be quickly covered or overturned by the real- time generated content. In the traditional architecture, there is a lack of an intermediate layer between online learning records and offline classroom activities that can accommodate generative content, making it difficult for teachers to effectively transfer the diverse outputs generated by AIGC online to offline discussions. This deficiency often leads to content discontinuity between the online and offline parts, resulting in high integration costs[1].

1.2 Redefinition and Functional Expansion of Course Elements by AIGC

1.2.1 Embedding Generative Literacy into Course Objectives

Generative literacy refers to learners' ability to effectively use AIGC to acquire, filter, reconstruct information, and judge its reasonableness. Traditional course objectives have not included such abilities, but as AIGC frequently intervenes in the learning process, if learners do not master prompt construction and result evaluation, they are prone to passively accepting generated content. Course objectives need to add measurable dimensions such as human- machine interaction strategies, habits of information tracing, and awareness of comparing multiple versions.

1.2.2 Transformation of Knowledge Units from Static to Dynamic

In the past, knowledge units existed in the form of textbook chapters or knowledge point cards, with clear and fixed boundaries. In the AIGC environment, the same core concept can generate multiple explanatory frameworks and application scenarios based on different queries. A knowledge unit is no longer a fixed piece of text but a set of generation rules and sample collections. Designers need to define the generation boundaries and constraints for each core concept, allowing dynamic generation while retaining manually reviewed typical examples.

1.2.3 Interactive Extension of AIGC as a Feedback Tool

Traditional feedback mainly comes from teacher grading, peer evaluation, or preset answering systems, with standardized content and high latency. AIGC can perform real- time semantic analysis on open - ended responses, assignment drafts, and discussion records, generate personalized improvement suggestions, and provide idea expansion or expression optimization. The extension of interaction is embodied in learners' ability to engage in multiple rounds of dialogue with AIGC, continuously revising their outputs until satisfaction is achieved.

1.3 Design of a New Morphological Structure for Blended Courses Based on Human-Machine Collaboration

1.3.1 Setting of Knowledge Base and Generation Boundaries

The underlying knowledge base comprises a core concept system, a collection of typical questions, and generation constraint rules. The core concept system describes the key terms that must be mastered in the course and their relationships in the form of a knowledge graph. The collection of typical questions provides common questioning styles and expected response directions for each knowledge point, serving as a reference for AIGC. The generation constraint rules specify the content types, expression styles, and citation norms that AIGC should not output. The design of this layer is completed in advance by course teachers, and is used to guide the output scope of AIGC and prevent generated content from deviating too far from the course objectives[2].

1.3.2 Real- Time Semantic Response in the Interactive Generation Zone

The middle interactive generation zone is the space where learners directly converse with AIGC. After learners' questions, assignment drafts, and discussion records are fed into AIGC, the system outputs personalized explanations, analogous cases, or extended materials according to the constraints of the underlying knowledge base. Real- time semantic response means that AIGC not only reacts to the current input but also adjusts its expression style and information density by integrating learners' historical interaction records. This zone simultaneously records every piece of generated content and its source, for later invocation by the reflection and integration layer.

1.3.3 Triggering of Differentiated Strategies in the Reflection and Integration Layer

The top- layer reflection and integration layer is responsible for guiding learners to compare the differences between their original understandings and the generated content. When learners stay in the interactive generation zone beyond a set threshold or repeatedly ask similar questions, the system automatically triggers reflection prompts, requiring learners to summarize the information they have currently mastered and to point out inconsistencies. At this layer, AIGC generates reflection frameworks or self- test questions to help learners integrate fragmented generated content into their personal knowledge structures. The differentiation of strategies is reflected in the fact that different learners adopt different reflection methods—some are suitable for list- based comparisons, while others are suitable for drawing concept maps—and AIGC automatically matches the corresponding integration tools according to learners' usage preferences.

2. Content Generation Mechanism and Adaptive Learning Paths for AIGC

2.1 Dynamic Construction of Course Knowledge Units Driven by Multimodal Semantic Generation

2.1.1 Node Triggering and Modality Alignment in Semantic Graphs

A core semantic graph for the course is maintained at the underlying level, with each node representing a knowledge point and edges denoting logical associations. When a learner's progress or a query points to a certain node, AIGC reads the semantic features and invokes multimodal interfaces to output explanatory texts, illustrative images, and audio narrations. Modality alignment requires that textual terms be consistent with the positions of image annotations, and that audio be synchronized with text highlights. This alignment is achieved through shared latent space representations, ensuring that the semantics of different modalities do not contradict each other[3].

2.1.2 Context-Aware Content Assembly Strategy

The same knowledge node requires different depths of expression and modality combinations at different stages. Context-aware assembly encodes learners' historical interactions, task types, and mastery levels into context vectors. AIGC accordingly extracts relevant nodes and selects appropriate modality combinations, such as using "text plus static images" for the novice stage, and switching to "text plus interactive simulations" for the advanced stage. The assembly process regenerates content so that the examples and parameters match the current context.

2.1.3 Version Iteration Mechanism for Dynamic Knowledge Units

Each generation produces a version record for the knowledge unit, including the generation time, the context vector, and subsequent feedback. When multiple learners show low accuracy rates or high help - seeking rates in similar contexts, AIGC triggers version iteration by adjusting generation parameters or adding explanation layers. The new version automatically replaces the old one for similar situations, while the old version is retained for comparison. This mechanism enables the knowledge unit to be gradually optimized with usage frequency, without the need for human intervention.

2.2 Content Difficulty and Sequence Adjustment Guided by Learners' Real - Time Interactive Feedback

2.2.1 Quantification and Mapping of Multidimensional Feedback Signals

Real- time feedback comprises three quantifiable dimensions: accuracy rate, response time, and help- seeking frequency. Each dimension is mapped to a scalar value in the[0,1] interval, and the values are weighted to form a comprehensive mastery coefficient. The mapping function employs an asymmetric sigmoid curve, where response times below the mean contribute more significantly, and help-seeking frequencies exceeding the threshold incur a more pronounced penalty. This coefficient serves as the direct input for difficulty adjustment.

2.2.2 Dynamic Adjustment Algorithm for Difficulty Thresholds

Each knowledge unit is preset with three difficulty levels, corresponding to foundational understanding, applied analysis, and comprehensive evaluation. The difficulty adjustment determines whether to upgrade or downgrade based on the mastery coefficient at the current difficulty level. When the coefficient exceeds 0.8 for three consecutive times, the difficulty is upgraded; when it falls below 0.4, the difficulty is downgraded and supplementary explanations are provided. The dynamic adjustment is reflected in the threshold drifting with overall performance: when continuous progress is made at higher difficulties, the upgrade threshold is lowered from 0.8 to 0.75, and vice versa[4].

2.2.3 Generation and Merging Rules for Temporary Branch Paths

When learners cannot proceed due to insufficient prerequisite knowledge, AIGC generates a temporary branch path that includes two to three prerequisite knowledge units. The length of the branch depends on the number of missing knowledge items, and each unit adopts the same generation mechanism as the main path. After completion, the branch is marked as mastered and automatically merged back to the main path node. The merging requires that the mastery coefficient of the branch reaches above 0.7; otherwise, the branch is extended or a more basic explanation is regenerated. This design ensures the integrity of the main path and fills the knowledge gaps.

2.3 Automatic Orchestration Method for Personalized Learning Paths Based on Generative Models

2.3.1 Learner State Representation under the Encoder-Decoder Structure

The model adopts an encoder-decoder architecture. The encoder receives the ability profile, the list of learned knowledge points, the current objective, and the records of the last ten interactions, concatenates them, and feeds them into a multi-layer Transformer, outputting a fixed-dimension hidden state vector. The decoder takes this vector as the initial state and gradually generates learning steps, each containing a knowledge point identifier, modality selection, and expected duration. The state representation also incorporates forgetting curve parameters, enabling the model to adjust its strategy according to the time of the last learning session and prioritize the review of content that is about to be forgotten.

2.3.2 Rolling-Style Path Generation and Constraint Injection

The path adopts rolling-style generation, generating only three to five steps at a time. After the learner executes them, new feedback is appended, and the encoder is rerun to update the hidden state, after which the next window of steps is generated. The constraint injection module ensures during decoding that important prerequisite knowledge points are not skipped and that content already mastered with a low forgetting coefficient is not repeated. The constraints use soft masking to lower the probabilities of violating steps without forcing them to zero, thus preserving room for exploration[5].

2.3.3 Performance-Driven Path Correction Mechanism

When a learner initiates help requests more than twice within a certain window or the accuracy rate falls below 0.5, path correction is activated. The model does not modify the current window; instead, it temporarily switches the objective to "consolidating weak points" during the next rolling generation. Correction methods include extending the number of current steps, lowering the subsequent difficulty, or inserting review tests. After the correction ends, the objective is switched back to the original coverage target. The correction records are retained and used to adjust parameters in advance for similar subsequent performance, thereby endowing the model with meta-learning capabilities.

3. Intelligent Turn and Dynamic Calibration of the Blended Course Evaluation System

3.1 Logical Shift of Course Evaluation from Outcome Measurement to Process Tracking

3.1.1 Expansion of Evaluation Granularity from Final Outputs to Behavioral Traces

Traditional evaluation collects one- time output data, losing a large amount of process information. Process tracking refines the granularity to each human - machine interaction event, including the length of question input, the viewing duration of generated results, the number of revisions, and the behaviors of adoption or rejection. These traces are encoded as event labels and timestamps, forming a behavioral trace sequence. The evaluation comprehensively examines the number of trial attempts, the ways of adjusting prompts, and whether the learner actively requests multiple rounds of explanations.

3.1.2 Process Data Modeling Method Based on Time Series

The behavioral trace sequence is characterized by high dimensionality, sparsity, and non- uniform time intervals. We adopt a Hidden Markov Model or a Transformer encoder to map events into a latent state space and extract three indicators: cognitive engagement level, confusion level, and strategy stability. The Hidden Markov Model divides the process into exploration phase, consolidation phase, and stagnation phase, and describes state transitions through transition probabilities. The sequence is compressed into a process vector, which is used for correlation analysis with course parameters.

3.1.3 Attribution Shift of Evaluation Conclusions toward Human - Machine Collaboration Strategies

Result measurement usually attributes conclusions to learners' own abilities. Process tracking allows attribution to specific collaboration strategies, such as the clarity of prompts, the ability to compare multiple results, and the reasonableness of follow- up questions. When the output is low, process data can show that the problem lies in overly broad prompts rather than insufficient knowledge. This attribution enables evaluation results to directly guide learners in improving their interaction with AIGC.

3.2 AIGC- Supported Collection and Integration of Diverse Performance Data

3.2.1 Design Method of Embedded Collection Triggers

Prompt - based tasks are embedded in course activities, requiring learners to leave traceable interaction records. The triggers are divided into active and passive types. Active triggers pop up a generation task after specific knowledge points (e.g., "Use AIGC to generate three analogies and choose the best one") and record the selection process. Passive triggers monitor dialogue turns and record a low - activity event when there is no substantive input for three consecutive rounds. All outputs are structured logs, containing trigger conditions, timestamps, and operation content[6].

3.2.2 Alignment Strategy for Heterogeneous Data in Shared Semantic Space

The collected data include formats such as text, numerical values, and time - series. We adopt contrastive learning to train a cross- modal alignment model, which maps text embeddings, response times, and clickstreams into a 128- dimensional semantic space. The supervisory signals come from a small number of manually annotated semantic labels. After the model is trained, different types of data can compute distances within this space. For example, when the embedding of a confused text is close to the embedding of an excessively long dwell time, they are fused into a "cognitive stalling" event.

3.2.3 Generation and Representation of Performance Data Profiles

The integrated data are used to generate performance data profiles, which comprise five dimensions: knowledge accuracy (adoption correctness rate), collaborative generation efficiency (number of problems solved per round), strategic diversity (number of prompt types), metacognitive regulation ability (number of active revisions), and innovative tendency (frequency of uncommon questions). The score of each dimension is presented as a time- series curve. The profiles are displayed in the form of radar charts with trend lines, and AIGC automatically annotates the intervals of significant changes along with the event contexts.

3.3 Closed-Loop Adjustment Strategy for Course Parameters Based on Real-Time Analysis Results

3.3.1 Construction and Latency Control of the Streaming Analysis Pipeline

The pipeline includes data ingestion, sliding window aggregation, feature calculation, and metric output. In the ingestion stage, data are written into a ring buffer at a granularity of one second. The multi-window aggregation maintains three windows of 5 minutes, 15 minutes, and 1 hour, corresponding to short-term, medium-term, and long-term trends. At the end of each window, the feature calculation computes the group average mastery coefficient, help-seeking rate, and adoption rate. Asynchronous batch processing controls the latency within 30 seconds to ensure timely feedback.

3.3.2 Mapping Rules from Course Parameters to Analysis Metrics

The mapping rules define the parameter adjustments triggered by the metrics. The first level concerns content parameters: when the group average adoption rate falls below 0.4, the generation complexity weight of the corresponding node is lowered and the number of examples is increased. The second level concerns difficulty parameters: when an individual's mastery coefficient decreases for two consecutive times, the difficulty is reduced by one level. The third level concerns path parameters: when over 25% of learners in the class have a help- seeking rate higher than 0.6, prerequisite review units are preferentially inserted. The rules are stored as key - value pairs and support dynamic modification.

3.3.3 Collaborative Update Mechanism of the Inner Loop and the Outer Loop

The closed- loop adjustment adopts a dual- loop structure. The inner loop runs in each session, making real- time fine- tuning adjustments to the content presentation mode (e.g., the level of detail in prompts) based on the metrics of the last five minutes. The adjustments made by the inner loop are local and reversible, and if the negative effects exceed the threshold, the system performs a rollback. The outer loop runs after the course ends, performing batch updates to the model parameters, the edge weights of the semantic graph, and the mapping thresholds based on all historical data. Before the outer loop update is deployed, a comparison of efficiency metrics between the new and old versions is conducted, and deployment occurs only when the positive improvement exceeds 5%. This mechanism balances real- time responsiveness with stable operation.

Conclusion

This study constructs an innovative framework for AIGC - based blended course construction models from three dimensions: theoretical foundations, content generation mechanisms, and evaluation systems. At the theoretical level, it identifies the bottlenecks of traditional architectures, introduces generative literacy and dynamic knowledge units, and proposes a three - layer human - machine collaborative structure. At the content and path level, it realizes the dynamic construction of knowledge units driven by multimodal semantics, the adjustment of difficulty and sequence guided by real- time feedback, and the adaptive orchestration of learning paths supported by generative models. At the evaluation level, it completes the logical shift from outcome measurement to process tracking, and designs strategies for multi- source data collection and integration as well as double- loop closed- loop adjustment. Future directions include: iterative optimization and parameter sensitivity testing of the model in real courses; cross- course semantic graph transfer methods to reduce construction costs; and in- depth investigation of the patterns of learners' metacognitive changes in human - machine collaboration.

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