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

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Abstract: *Generative artificial intelligence is changing the form of teaching materials, and the old model of blended learning courses can no longer meet the new demand for pre-set modules, linear interaction and fixed assessments. The purpose of the three new ideas in this paper is to put forward new ideas for the model of blended courses with AIGC, build a three-level system for identifying problems in traditional architecture, redefine course elements, design a three-tier structure for human-machine collaboration, develop a dynamic construction method for knowledge units based on multimodal semantics, apply adaptive path orchestration with real-time feedback and generative models, promote a change in assessment from measuring outcomes to observing processes by collecting all kinds of data and AIGC, and establish streaming analysis and double-loop closed-loop adjustment methods. The above offer the theoretical and technical basis for the adaptive construction of blended courses.*

Keywords: *Generative Artificial Intelligence, Blended Courses, Human-Machine Collaboration, Adaptive Learning Paths, Process Evaluation*

Introduction

Blended courses have long been based on pre-recorded knowledge modules and fixed modes of interaction, and teachers have had relatively little control over content creation and learning paths. AI can create and modify teaching materials in real time for different students during class, and with the help of intelligent systems, students will be freed from traditional modes of learning. The two problems are as follows: First, the current course architecture does not meet the demands of all kinds of generative content and the requirement for non-linear dialogue, and there is no buffer for online-offline integration. Second, the assessment system only knows the final scores and does not record how the students behaved or what strategies they used in cooperation with computers. Therefore, we need to systematically innovate the construction model of blended courses so that they can effectively integrate the generative capabilities of AIGC and maintain the guidance of course objectives and the accuracy of evaluation. The goals of this paper are to redefine the components of a course at the theoretical level, design the content generation and path adaptation mechanism in a technical manner, build process tracking and dynamic calibration systems for evaluation, and thus present a complete model framework for the transformation of blended courses in the era of AIGC.

1. Theoretical Basis and Structural Reform of AIGC Integration in Blended Courses

1.1 Adaptive Bottlenecks of Traditional Blended Course Architectures in Generative Environments

1.1.1 Temporal Conflict between Preset Modules and Generated Content

After the online materials have been created as static text or videos, it is not easy to integrate them with the information generated in real time by AIGC. If the students begin to ask open-ended follow-up questions about the pre-loaded material, the answers provided by AIGC may be too general and thus reduce the pace of learning. The pre-set exercises in the module will not cover the new knowledge obtained from the generated content, so learners need to switch back and forth between the two systems repeatedly and will have to exert more cognitive effort.

1.1.2 Constraints of Linear Interaction Paths on Dynamic Demand

The communication path of the traditional blended course is generally one-way; students need to click through the courseware, answer questions, and then submit them one by one. Although the non-linear dialogue mode of AIGC can change topics or ask for more information at any time, the course system is still based on a fixed menu and is therefore not suitable. After generating the dialogue, the students need to return to the start of the original path, and their previous learning rhythm and concentration are often gone.

1.1.3 Lack of a Buffer for Online-Offline Integration

Teachers can have AI create discussion materials for offline classes, and thus, the original set of questions will be covered or extended in real time by this new content. Traditional schools do not have an intermediary link to store the online learning records and offline classroom activities that support generative content, so it is difficult for teachers to present all the various outputs generated by AIGC online in offline discussions effectively. It may be that the online and offline content are out of sync, and the coordination cost will be too high[1].

1.2 Redefinition and Functional Expansion of Course Elements by AIGC

1.2.1 Embedding Generative Literacy in Course Objectives

Generative literacy is the ability of learners to use AIGC to obtain, organise, revise and evaluate information reasonably. Although it was not one of the original goals, given that AIGC is frequently used in class, if students do not know how to write prompts and evaluate the results, they will probably become passive recipients of the generated content. Set particular goals for the course objectives, such as strategies for human-machine collaboration, habits of information management, awareness of different versions, etc.

1.2.2 Transformation of Knowledge Units from Static to Dynamic

In the past, the knowledge units were in the form of textbook chapters or knowledge point cards, and they had clear and fixed boundaries. The same basic idea of AIGC can be used to create many explanation frameworks and application cases for different questions. A knowledge unit is no longer a fixed piece of text but a set of generation rules and sample collections. Set the generation boundaries and constraints for each core concept in the Design, and keep some of the typical examples that have been manually verified.

1.2.3 Interactive Extension of AIGC as a Feedback Tool

The original feedback channels are the teacher's grades, peer assessments and so on; they are standardised and slow. AI can be used to answer open-ended questions, provide homework and discussion notes in real time, offer personalised improvement advice, and give new ideas or other ways of expression. The extension of interaction can be shown by the students' ability to have multiple rounds of conversation with AIGC and repeatedly revise their work until they are satisfied.

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 foundation of the knowledge base is a core concept system and a set of typical questions and generation constraint rules. The core concept system provides the necessary knowledge points that need to be learned in the course and shows how they are connected in a knowledge graph. A set of typical questions can provide some reference for the form and direction of answers to all kinds of knowledge in AIGC. Generation constraint rules specify the types, expressions and citation norms of the content that AIGC should not generate. The design of this layer will be in advance by the course teacher to guide the output scope of AIGC and prevent the generated content from deviating too much from the goals of the course[2].

1.3.2 Real-Time Semantic Response in the Interactive Generation Zone

The middle interactive generation area is the place where students can speak directly with AIGC. Obtain the questions, assignment drafts and discussion records from the learners, then have AIGC generate personalised explanations, analogous cases or extended materials based on the constraints of the underlying knowledge base. Real-time semantic response is the ability of AIGC to change the style and quantity of information in its answers based on previous interactions with learners. The area above will collect all the generated content and its sources, and then use them in the reflection and integration stage.

1.3.3 Triggering of Differentiated Strategies in the Reflection and Integration Layer

The top-layer reflection and integration module will have students compare their initial thoughts with the knowledge they have gained from the material. If the learners remain in the interactive generation area for a long time or repeatedly ask the same question, a reflection prompt will be displayed automatically to have them summarise what they have learned so far and check for any inconsistencies. AIGC can build a reflection framework or self-assessment questions at this time to help students organise the scattered generated content in their own knowledge system. The different strategies can be seen from the fact that various learners choose different reflection methods; some are suitable for list-based comparisons, others are suitable for drawing concept maps, and AIGC will automatically select the corresponding integration tool based on how these learners use it.

2. Content Generation Mechanism and Adaptive Learning Paths for AIGC

2.1 Dynamic Construction of Course Knowledge Units Based on Multimodal Semantic Generation

2.1.1 Node Triggering and Modality Alignment in Semantic Graphs

At the basic level, a fundamental semantic graph of the course is built, and every node is a piece of knowledge and every edge is a logical relationship. When the learner has made some progress or has a question, that node will be selected by AIGC, and then multimodal interfaces will be employed to generate explanatory text, illustrative pictures and audio narration. Modality alignment needs to match textual terms with the locations of image annotations, and audio should be aligned with text highlights. The above way is to use a common latent space representation so that the meaning in the two modalities is consistent[3].

2.1.2 Context-Aware Content Assembly Strategy

The same knowledge node requires different depths of expression and modality combinations at different stages. Contextual Assembly puts the history of learner interaction, task type and mastery level into context vectors. Then AIGC will extract the corresponding nodes and select an appropriate combination of modalities, such as "text and static images" for the beginner level and "text and interactive simulations" for the advanced level. Assembly will add new content and revise the examples and parameters according to the current circumstances.

2.1.3 Version Iteration Mechanism for Dynamic Knowledge Units

Each generation creates a version record of the knowledge unit and, at the same time, stores the generation time, context vector, and so on. When many learners have low accuracy or frequently ask for help in the same situation, AIGC will increase the number of versions or add explanations. The new one will replace the old one in the same way and save the old version for comparison. Therefore, with the help of the above method, the knowledge unit can be automatically strengthened according to how often it is used.

2.2 Based on the current feedback from the students, modify the difficulty and order of the content

2.2.1 Quantification and Mapping of Multidimensional Feedback Signals

The three indicators of timely feedback are the accuracy rate, response time and frequency of help-seeking. Each dimension is mapped to a scalar in the range[0, 1], and then these values are given weights to calculate a total mastery coefficient. The mapping function is an asymmetric sigmoid curve; that is to say, response times below the mean are given more weight, and help-seeking frequencies above the threshold are penalized more severely. The above coefficient is used to set the difficulty directly.

2.2.2 Dynamic Adjustment Algorithm for Difficulty Thresholds

The three levels of difficulty for the knowledge units have been set as basic understanding, application and analysis, and generalisation. Adjust the difficulty by increasing or decreasing it according to how well the student knows it at the present time. If the coefficient is greater than 0.8 three times in a row, it will be considered difficult; if it drops below 0.4, it will be regarded as easy and extra explanations will be provided. The change is that the threshold will be adjusted according to the general performance; if there has been continuous progress at a high difficulty level, the upgrade threshold will be reduced from 0.8 to 0.75, and so on[4].

2.2.3 Generation and Merging Rules for Temporary Branch Paths

If the students cannot continue because of a lack of the necessary prerequisite knowledge, AIGC will create a temporary branch and two or three related sections. The length of the branch is determined by the number of missing knowledge items, and each unit has the same generation mechanism as the main path. Finally, mark the branch as mastered and automatically merge it back into the main path node. The merger should have a mastery coefficient for the branch greater than 0.7; otherwise, the branch will be extended or a more basic explanation will be provided. The Design above will cover the main cases and deal with the others.

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

2.3.1 Learner State Representation in the Encoder-Decoder Structure

The Model is an encoder-decoder model. The encoder obtains the ability profile, the list of learned knowledge points, the current objective and the record of the last ten interactions; concatenating them, it is then passed to a multi-layer Transformer to obtain a fixed-size hidden-state vector. The decoder takes the above vector as its start and incrementally adds learning steps, and each learning step has a knowledge point ID, modality selection and expected duration. The state also has forgetting curve parameters to adjust the strategy based on how long it has been since the last learning session and prioritise revising content that is about to be forgotten.

2.3.2 Rolling-Style Path Generation and Constraint Injection

It is an endless production, and only three or four stages are produced at a time. After the learner executes them, new feedback is added, the encoder is run again to update the hidden state, and then the next window of steps is generated. The constraint injection module will make sure that all the necessary prerequisite knowledge points in the decoding are available, and content with a low forgetting rate will not be repeated. A soft mask is used to reduce the probability of a step violation but not to eliminate it, so some exploration can still be carried out[5].

2.3.3 Performance-Oriented Path Correction Mechanism

If a student has asked for help more than twice in a short period and has answered correctly less than 50% of the time, then path correction will be applied. It will not change the current window, but will temporarily set the objective to "consolidating weak points" for the next rolling period instead. Correction Methods are to increase the number of current steps, decrease the next difficulty, or add review tests. A correction has been made, and now we will work to achieve the original coverage goal. Save the corrected information, and based on it, pre-adjust the parameters for the next similar performance in meta-learning of the model.

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 Broadening the Granularity of Evaluation from Final Results to Behavioural Traces

The last one only saved the final results and did not record the process. Process tracking has been improved to some extent, and now it records how long it takes to add a question, how long the generated results have been viewed, how many times they have been revised, and whether they have been approved or rejected. The above traces are labelled as events and timestamps, and they form a sequence of behaviour. Collect all the trial counts, the different ways to modify the prompts, and whether the student voluntarily asks for several repetitions of the explanation.

3.1.2 Process Data Modeling Method Based on Time Series

The sequence of behaviour traces has a large number of dimensions and is sparse and irregular in time. A Hidden Markov Model or a Transformer encoder is used to map the events into a latent state space, and then the three indicators of the level of cognitive engagement, degree of confusion and stability of strategy are extracted. The three periods of a Hidden Markov Model are exploration, consolidation and stagnation, and the switches between these periods are given by transition probabilities. Based on the order, a process vector is constructed and then used in the correlation analysis of course parameters.

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

The results are generally considered the students' own achievements. Process tracking can help us find out why the cooperation has not achieved the desired results at a certain time; for example, there may be an ambiguous prompt, a lack of comparison with other results, or unreasonable follow-up questions. If the output is low, it may be that the problem with the prompt is too general, and it is not a lack of knowledge. Therefore, the results of the assessment can be used to improve how learners use AIGC.

3.2 AIGC-Assisted Collection and Integration of Various Performance Data

3.2.1 Design Method for Embedded Collection Triggers

Add prompted tasks to the lesson content and have students record the results of their exploration. There are two kinds of triggers: active and passive. Active Triggers will show a generation task after reaching a certain knowledge point (e.g., "Use AIGC to generate three analogies and select the best one") and log the selection process. Passive triggers will be idle for a few seconds after the end of the dialogue and will not be triggered by user input. All output is structured log that contains the trigger condition, timestamp and operation information[6].

3.2.2 Alignment Strategy for Heterogeneous Data in Shared Semantic Space

The collected data are in many forms, such as text, numbers and time series. Contrastive learning is used to train a cross-modal alignment model that maps text embeddings, response times and clickstreams into a 128-dimensional semantic space. The supervisory signals are a small number of manually annotated semantic labels. Train the model and then calculate the distance of all the data in this space. For example, if the embedding of the confused text is close to the embedding of an excessively long dwell time, they will be combined to form a "cognitive stalling" event.

3.2.3 Generation and Representation of Performance Data Profiles

Based on the above data, performance data profiles have been built, and these profiles consist of the following five indices: 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 scores of all these indicators are shown in time-series graphs. It is a radar chart with a trend line, and AIGC will automatically add annotations for the interval of a significant change and the context of that event.

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

3.3.1 Construction and Latency Control of the Streaming Analysis Pipeline

The four are: Data Input, Sliding Window Aggregation, Feature Engineering and Metric Output. At the time of ingestion, the data will be written to a ring buffer every second. The three windows of the multi-window aggregation are 5 minutes, 15 minutes and 1 hour; they correspond to the short-term, medium-term and long-term trends. At the end of each window, calculate the group average mastery coefficient, help-seeking rate and adoption rate in the feature calculation step. The delay of the asynchronous batch process is 30 seconds, and then it will be released.

3.3.2 Mapping Rules from Course Parameters to Analysis Metrics

The rule of mapping is to modify the parameters according to the index. The first level is about content parameters; if the group's average adoption rate is less than 0.4, then the generation complexity weight of that node will be reduced and the number of examples will be increased. The second level is the difficulty parameter; if the person's mastery coefficient decreases by one each time, then the difficulty is reduced by one level. The third level is path parameters; if more than 25 per cent of the students in the class have a help-seeking rate above 0.6, prerequisite review units will be added first. A RuleForm is a kind of key-value that can be changed dynamically.

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

The outer loop is a closed-loop correction. In each round, an inner loop is employed to dynamically modify the display mode of the content (e.g., the level of detail in the prompts) according to the statistics of the past five minutes. The correction in the inner loop is local and reversible; if it has a serious negative effect, then a rollback will be carried out. The outer loop is run after each round to perform a batch update of the model parameters, the edge weights in the semantic graph and the mapping thresholds based on all the historical data. Before deploying the update in the outer loop, compare the efficiency indicators of the new and old versions, and only if the improvement is more than 5%, deploy it. Therefore, there will be both timeliness and stability.

Conclusion

The three parts of the new framework for AIGC-based blended course construction models in this paper are the theoretical basis, the content generation mechanism and the evaluation system. The problems of the old model have long been known, and now new ideas for generating knowledge under human guidance have been put forward. At the level of content and path, dynamic knowledge units can be constructed based on multimodal semantics, and according to feedback, both the difficulty and order can be adjusted in real time, and learning paths can be organised flexibly with the help of generative models. At the level of evaluation, one can observe the results, monitor the progress of implementation, design plans to collect and integrate data from all sides, and carry out a double-loop closed-loop correction. Next, we will further improve the model, study the effect of parameters in actual classes, learn about cross-course semantic graph transfer methods to reduce construction costs, and gain more knowledge on changes in learners' metacognition during human-machine collaboration.

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