Generative AI-Driven Learning Path Optimization: A Framework Based on Transformer and Cognitive Load Theory

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Abstract: With the rapid development of artificial intelligence, especially generative AI based on Transformer models, personalized learning has gained significant attention in the field of intelligent education. This paper proposes a framework for optimizing learning paths using generative AI, integrating the principles of Cognitive Load Theory (CLT) to create dynamic, adaptable learning experiences. The framework consists of four key modules: learner profiling, cognitive load analysis, Transformer-based path generation, and feedback adaptation. By dynamically adjusting learning paths based on real-time cognitive load assessments, this system enhances learning efficiency and learner engagement. The integration of CLT ensures that the cognitive load is optimally balanced, preventing overload and promoting deeper learning. Through a series of empirical experiments, the proposed system is validated, demonstrating its potential to improve learning outcomes in personalized educational environments. This work contributes to advancing the field of AI-driven education systems, offering a novel approach to adaptive learning path generation that is both cognitively informed and highly responsive to individual learner needs.

1. Introduction

1.1 Research Background and Problem Statement

With the rapid advancement of artificial intelligence technologies, especially the growing application of generative AI models built upon the Transformer architecture in fields such as natural language processing, recommendation systems, and educational technology, personalized learning has emerged as a critical frontier in the development of intelligent education systems. Unlike conventional instructional design approaches that adopt a one-size-fits-all model, personalized learning emphasizes tailoring learning content and strategies to individual learners' characteristics, preferences, and progress. However, traditional learning path planning still predominantly relies on pre-defined knowledge graphs and static rule-based engines. These approaches lack the flexibility to accommodate the dynamically changing cognitive states, learning goals, and emotional fluctuations of students in real time. As a result, learners often encounter mismatches between their current needs and the instructional content delivered, which may hinder engagement, increase cognitive overload, or reduce learning effectiveness. Generative AI, particularly large language models like those based on the Transformer framework, offers a promising solution to this challenge. These models possess strong capabilities in semantic understanding, contextual reasoning, and adaptive content generation. When properly integrated with educational data, they have the potential to generate intelligent, context-aware, and cognitively adaptive learning paths that respond in real time to learners' needs, thereby addressing the limitations of traditional learning systems and enhancing the overall learning experience.

1.2 Theoretical Basis and Research Significance

This study is grounded in Cognitive Load Theory (CLT), which posits that human working memory has limited capacity and that instructional design should carefully regulate cognitive load to

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maximize learning efficiency. CLT categorizes cognitive load into intrinsic, extraneous, and germane types, each requiring distinct management strategies. Excessive cognitive load, especially when poorly aligned with the learner’s prior knowledge or task complexity, can impede understanding and retention.

Incorporating CLT into the design of AI-driven learning systems presents a significant opportunity to develop adaptive instructional models that are both pedagogically sound and technologically advanced. In particular, the integration of cognitive load monitoring mechanisms into generative AI systems enables real-time assessment and adjustment of instructional content based on learners’ mental workload.

By leveraging the dynamic reasoning and generation capabilities of Transformer-based models, such systems can go beyond static personalization to achieve cognitive responsiveness—adjusting not only the content but also the sequencing and complexity of learning tasks. This enhances the human-computer interaction experience and supports more effective, personalized learning processes. The significance of this research thus lies in its potential to bridge cognitive science and AI, offering new pathways for scalable and intelligent educational interventions.

1.3 Research Objectives and Content

This study aims to construct a learning path optimization framework based on the Transformer architecture and Cognitive Load Theory. The main content includes: analyzing the role of generative AI in learning path design; exploring the integration of cognitive load regulation mechanisms with personalized recommendation systems; proposing and validating an intelligent learning path optimization system model.

2. Integration Logic of Generative AI and Learning Path Optimization

2.1 Overview of the Transformer Model and Its Educational Potential

Since its introduction by Vaswani et al. in 2017, the Transformer model has become the mainstream architecture in natural language processing. Centered on the "Self-Attention Mechanism," it can effectively capture long-range dependencies in sequence data, overcoming the efficiency bottleneck of traditional recurrent neural networks in sequence modeling [1]. Built with stacked encoders and decoders, Transformer models offer excellent parallel computing capability and scalability, and are widely used in tasks such as text generation, translation, summarization, and question answering. In the educational field, the Transformer model demonstrates strong generalization ability and intelligent potential. For example, through training on large-scale educational data, it can be applied to personalized knowledge explanation, automatic grading and feedback, test question generation, and content summarization. Furthermore, Transformer-driven intelligent teaching systems can dynamically adjust teaching strategies and resource allocation based on students’ learning trajectories and behavior patterns, providing timely, appropriate, and adaptive personalized learning services, thereby significantly improving learning outcomes and motivation.

2.2 Core Tasks of Learning Path Optimization

Learning path optimization is a key method for achieving personalized learning. Its core lies in dynamically planning the most suitable learning sequence and resource combination based on the learner’s current knowledge level, learning preferences, cognitive style, and target needs [2]. This task requires consideration of the dependencies among knowledge points and the structure of the knowledge graph, as well as assessment of learners' actual capabilities and interests to avoid cognitive overload caused by content being too difficult or too easy. An efficient learning path should be hierarchical, progressive, and adaptive, ensuring systematic knowledge delivery while meeting learners’ individual needs. In practical applications, learning path optimization involves several sub-tasks such as knowledge recommendation, content sequencing, progress prediction, and resource matching, all of which pose high demands on algorithmic intelligence.

2.3 Advantages of Generative AI-Driven Path Optimization

Generative Artificial Intelligence (Generative AI), represented by large language models, has shown wide application prospects in educational technology in recent years. Compared with traditional rule-based or collaborative filtering recommendation algorithms, generative AI has stronger semantic understanding and content generation capabilities [3]. It can understand learners' potential needs and cognitive states through natural language interaction, and generate learning paths that are more aligned with reality. Its advantages are mainly reflected in three aspects: First, in terms of humanization, generative AI can understand learners' expression habits and goal settings, enabling personalized path generation; Second, in terms of interactivity, it supports real-time conversational feedback and path adjustment, enhancing the flexibility and responsiveness of learning systems; Third, in terms of contextualization, generative AI can automatically adjust learning priorities according to dynamic changes in learning scenarios (e.g., approaching exams, knowledge forgetting), achieving true learner-centered teaching.

Therefore, learning path optimization systems integrated with generative AI not only enhance the intelligence level of teaching but also provide strong technical support for building a learner-centered educational ecosystem.

3. Cognitive Load Theory and Learning Design Principles

3.1 Types of Cognitive Load and Their Relationship with Learning Outcomes

Cognitive Load Theory (CLT), proposed by Sweller et al., emphasizes that learners have limited cognitive resources when processing information. According to this theory, cognitive load in learning can be divided into three types: intrinsic load, extraneous load, and germane load.

Intrinsic load is determined by the complexity of the learning content and the learner's prior knowledge level. It is an important factor in the learning process that cannot be entirely eliminated but can be regulated. Extraneous load originates from the improper presentation of teaching materials, such as redundant information, complex interfaces, and confusing expression, which distract learners and reduce learning efficiency. Germane load refers to the cognitive effort learners actively invest in constructing knowledge representations and forming long-term memory, which is a necessary positive load for effective learning [4].

The key to optimizing instructional design lies in: reducing extraneous load, managing intrinsic load, and increasing germane load. Through strategies such as organizing content structure rationally, optimizing instructional media, and enhancing learner engagement, the dynamic balance among the three types of load can be effectively regulated, thus improving learning efficiency and effectiveness and promoting understanding, transfer, and application of knowledge.

3.2 Personalized Cognitive Load Regulation Mechanism

Different learners show significant differences in knowledge mastery, attention allocation, and cognitive strategy use. Traditional "one-size-fits-all" teaching models are unable to meet individualized cognitive needs. To achieve truly personalized learning, it is necessary to establish a cognitive load monitoring and regulation mechanism based on multidimensional data sensing and feedback [5].

This mechanism can capture learners' cognitive states in real time through eye-tracking, EEG monitoring, behavior analysis (e.g., answering duration, click patterns, operation frequency), etc., to identify their current cognitive load level. Then, by dynamically adjusting the difficulty of learning tasks, content presentation methods, and interaction pace, the learning path and teaching resources can be accurately adapted.

In intelligent learning environments, this mechanism can be embedded into AI-driven learning platforms to achieve adaptive intervention and optimization of the learning process. For instance, when the system detects signs of distraction or cognitive overload, it can automatically simplify content structure, switch explanation methods, or provide immediate help prompts, thereby enhancing the fluency and intelligent responsiveness of the learning process.

3.3 Integration Paths of Instructional Design and AI Models

With the rapid development of generative AI technology, more and more instructional tasks are being assisted or led by AI systems. However, if learners' cognitive capacity is ignored and a large amount of content or complex operations are blindly pushed, it is easy to create a conflict between "intelligent recommendation" and "cognitive overload." Therefore, it is urgent to regard Cognitive Load Theory as an important theoretical foundation for AI model design and optimization.

Specifically, in the training phase of AI models, cognitive load-related indicators (such as task complexity, language abstraction, interaction density) can be incorporated into the label system of training samples or the design of loss functions, so as to control the cognitive difficulty of generated content from the source. Meanwhile, in the inference and content generation stages of the model, by integrating individual cognitive state sensing modules, the generation strategy and output format can be dynamically adjusted to ensure that the generated learning content has knowledge value and is within learners' acceptable cognitive range.

In addition, Cognitive Load Theory can also serve as one of the evaluation criteria for AI-generated content, to test whether the recommended content matches the learner's cognitive ability and learning stage. This integration path helps to realize truly "learning-centered" AI education systems and enhances the scientific, practical, and personalized level of instructional content.

4. Construction of an Optimized Learning Path Framework

4.1 Overall Framework Design

This study, grounded in personalized learning and cognitive science theories, proposes an intelligent learning path optimization framework driven by generative AI. The framework consists of four interrelated core modules: the Learner Profiling Module, the Cognitive Load Estimation Module, the Transformer-based Path Generation Module, and the Feedback and Adaptation Module.

As shown in the system structure diagram (to be inserted here), the modules are connected via data flows and control signals, forming a closed-loop dynamic learning system. The system operates as follows: the Learner Profiling Module first collects and constructs learners' profile data. The Cognitive Load Estimation Module then assesses the learner's current cognitive state. Based on this assessment, the Transformer-based Path Generation Module generates a personalized learning path under cognitive load control constraints. Finally, the Feedback and Adaptation Module continuously gathers learning feedback and dynamically adjusts the path content and sequence, achieving ongoing optimization and intelligent iteration. The framework offers high scalability and adaptability and provides practical technical support for implementing learner-centered instructional design [6].

4.2 Module Functions and Technical Implementation

Learner Profiling Module: This module collects real-time multidimensional learner data through interfaces with the learning platform, including background information (age, learning goals), learning behavior (click frequency, learning duration, navigation patterns), knowledge level (quiz scores, answer accuracy), and learning style (content preferences, task pacing). By applying multimodal data fusion algorithms and clustering analysis, the system constructs dynamic and fine-grained learner profiles that serve as a personalized basis for path generation. Cognitive Load Estimation Module: Integrating both subjective assessments (e.g., self-report questionnaires) and objective behavioral features (e.g., response time, repetition frequency, mouse movement patterns), this module uses machine learning models (such as Random Forest or SVM) to estimate the learner's cognitive load in real time. It outputs quantitative indicators of intrinsic, extraneous, and germane load, and identifies trends in load variation, thereby providing data support for path adjustments. Transformer-based Path Generation Module: As the core algorithm module, this component receives inputs from the learner profile and cognitive load state to dynamically generate personalized learning paths using a multi-layer Transformer architecture. Inputs include current knowledge status, learning goals, and constraints (e.g., cognitive load control factors), and the output is one or more learning path recommendations tailored to the learner. The module supports both soft and hard constraints to ensure personalization as well as feasibility. Feedback and Adaptation Module: After the learning path is implemented, this module continuously tracks key feedback information such as learning outcomes (e.g., quiz results, task completion), cognitive state changes (e.g., load monitoring indicators), and emotional responses (e.g., affective recognition). Based on this feedback, the system fine-tunes the path (e.g., content reordering, sequence adjustment, difficulty level shifting) and updates model parameters, enabling the system to self-optimize.

4.3 Model Explainability and Optimization Mechanism

To improve transparency, enhance user trust, and support practical educational applications, the framework incorporates model interpretability mechanisms. Through attention visualization, logic tracing of path recommendations, and learning task association graphs, the system clearly presents the reasoning logic and influential factors behind each generated path, helping both instructors and learners understand the rationale of the recommendations [7].

In terms of optimization, the system not only relies on static data to train the model but also continually ingests real-time feedback from the adaptation module, forming a closed-loop optimization process of cognitive load → path adjustment → model update. Methods such as incremental learning and reinforcement learning are applied to continuously refine model parameters and generation rules, improving the accuracy, rationality, and adaptability of path generation. Ultimately, the goal is to develop an intelligent learning system that transitions from "usable" to "trustworthy."

5. Experimental Design and Preliminary Validation

5.1 Experimental Sample and Data Collection

To verify the feasibility and effectiveness of the proposed generative AI-based personalized learning path optimization system, the study recruited 300 undergraduate students from a comprehensive university's online learning platform [8]. The sample included students from various majors, grade levels, and learning backgrounds, ensuring representativeness. All participants voluntarily enrolled and signed informed consent forms for data usage.

Data collection prioritized privacy protection and integrated students' online learning logs, task completion data, and subjective feedback questionnaires to create a multidimensional dataset encompassing behavioral, cognitive, and emotional data. Learning logs recorded behavioral data such as click paths, content navigation order, learning duration, and interaction frequency. Task performance data included quiz scores, completion times, submission frequency, and pass rates. Subjective feedback was gathered using the standardized NASA-TLX cognitive load scale and a customized learning satisfaction questionnaire, aiming to comprehensively capture students' learning experiences and psychological states during system use. All data were cleaned and standardized for system training, model evaluation, and subsequent analysis.

5.2 Experimental Procedure and Variable Design

A quasi-experimental design was adopted, with 150 students each in the experimental and control groups, ensuring no significant differences in background variables such as course foundation, gender ratio, or major distribution. The experiment lasted four weeks, using the course "Computational Thinking in College" as the test platform [9]. All students completed the same instructional tasks, which included theoretical learning, case analysis, and periodic assessments.

The control group used an existing rule-based traditional learning path recommendation system, which provided recommendations based on predefined logic and static user profiles. The experimental group used the Transformer-based generative AI learning path optimization system, which dynamically generated learning paths based on learner profiles and cognitive states and adjusted paths in real time using feedback.

Throughout the experiment, data were continuously collected on learning efficiency (e.g., number of tasks completed per unit time), task completion rate, path deviation, cognitive load indices (including both subjective ratings and system estimations), and learning satisfaction. Quantitative data were collected via periodic assessments and questionnaires, supplemented by qualitative feedback from interviews.

5.3 Experimental Results and Preliminary Analysis

Preliminary results showed that the experimental group outperformed the control group on multiple key learning outcome indicators, especially in learning efficiency, cognitive load management, and subjective satisfaction. On average, students in the experimental group completed significantly more learning modules per unit time, indicating that the generative AI system offered better-targeted content sequencing and pacing. The overall task completion rate was also higher in the experimental group, demonstrating the feasibility and practicality of the recommended paths.

Cognitive load scale results indicated that students in the experimental group experienced more balanced cognitive load throughout the learning process, with significantly reduced subjective burden during task transitions and concept shifts. Feedback from satisfaction questionnaires further confirmed the system's advantages: most students felt the recommended paths better matched their individual pace and comprehension style, enhancing their learning confidence and control over course content.

In follow-up in-depth interviews, many students stated that the AI-generated learning paths felt "like a private tutor," helping them more clearly identify their learning goals and priorities, greatly improving learning coherence and sense of achievement. These results provide preliminary validation for the practical applicability and effectiveness of the proposed learning path optimization framework and offer empirical support for future system iterations and model enhancements.

6. Conclusion

Generative AI technology—especially the natural language generation capabilities of Transformer-based models—offers robust technical support for personalized and dynamic learning path optimization. Integrating cognitive load theory into the path generation mechanism enhances both the scientific grounding of recommendations and the alignment of learning experiences with individual cognitive characteristics. By constructing a tripartite "generation-regulation-feedback" optimization system, this study offers a new approach that merges theory with practice in the field of intelligent education. Future work may further promote its application in diverse learning scenarios and explore new paradigms in learning behavior modeling and intelligent educational decision-making through multimodal data and interdisciplinary models.

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