

AI Course Generator: An Intelligent System for Automated and Personalized Course Creation

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Abstract - The rapid growth of online education has created a demand for scalable and personalized course creation systems. Traditional manual course design is time-consuming and often fails to adapt to diverse learner needs. This paper presents an AI Course Generator that automates course creation using artificial intelligence, natural language processing, and reinforcement learning. The system analyzes learner inputs such as topic, skill level, and learning objectives to generate structured modules, lessons, and assessments. A reinforcement learning-based feedback loop continuously optimizes course sequencing based on learner engagement and performance. Experimental evaluation using simulated learner data demonstrates improved engagement, faster course completion, and enhanced personalization compared to rule-based approaches. The proposed framework offers a scalable and adaptive solution for modern digital learning environments.

Index Terms - AI Course Generator, Adaptive Learning, Reinforcement Learning, Personalized Education, NLP, E-Learning Automation

I. INTRODUCTION

Personalized education has become essential in modern digital learning environments. However, traditional course creation methods are manual, time-intensive, and difficult to scale. Learners often struggle to find structured content aligned with their skill levels and goals. Artificial intelligence offers the potential to automate and personalize course generation. This paper proposes an AI Course Generator that dynamically creates learning content and continuously adapts it using reinforcement learning.

II. PROBLEM STATEMENT

Manual course development lacks scalability and personalization, resulting in inefficient learning experiences. Static course structures fail to adapt to individual learner progress and preferences. An intelligent automated system is required to generate adaptive, learner-centric educational content efficiently.

III. OBJECTIVES AND SCOPE

The objectives of this research are:

- To automate course generation using AI and NLP techniques.

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- To personalize learning paths based on learner profiles.
- To optimize course sequencing through reinforcement learning.
- To reduce instructor workload while maintaining content quality.

IV. RELATED WORK

AI-driven education systems have gained increasing attention. Sutton and Barto established foundational reinforcement learning principles for adaptive decision-making. Liu et al. applied reinforcement learning to personalized learning path recommendation. Surveys in adaptive e-learning highlight the limitations of static personalization models, motivating dynamic feedback-based approaches.

V. PROPOSED METHODOLOGY

A. System Architecture

The system consists of three core modules:

- 1) **Content Extraction Module:** Collects relevant educational material from open resources.
- 2) **Course Generation Engine:** Uses pretrained transformer models for topic segmentation, module creation, and assessment generation.
- 3) **Adaptive Feedback Loop:** Employs reinforcement learning to optimize course sequencing based on learner interaction data.

B. Mathematical Modeling

The reinforcement learning reward function is defined as:

$$R_t = \alpha L_t + \beta E_t + \gamma C_t$$

where L_t represents learner engagement, E_t assessment performance, and C_t course completion rate.

The Q-learning update rule is:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta [R_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

Unlike rule-based systems, the proposed framework dynamically adapts learning paths in real time based on continuous feedback.

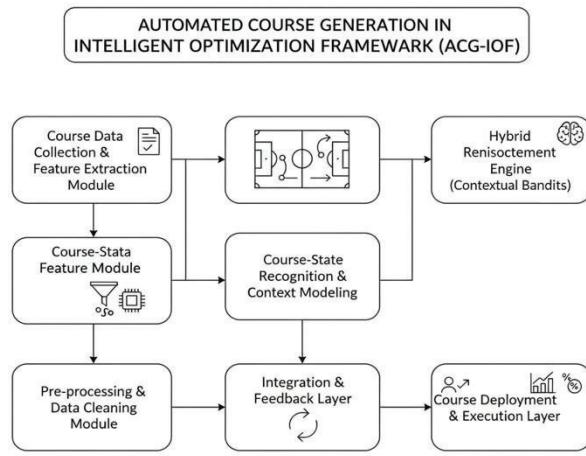


Fig. 1. AI Course Generator System Architecture

VI. EXPERIMENTAL SETUP AND EVALUATION

A. Dataset Description

Due to the lack of publicly available datasets for automated course generation, a synthetic dataset was created. It consists of 500 simulated learners characterized by prior knowledge level, learning pace, content preference, and assessment performance. Approximately 3,000 learner–course interaction instances were generated.

B. Experimental Configuration

The system was implemented in Python using TensorFlow. A Deep Q-Network (DQN) was employed as the learning agent. The state space included learner attributes and historical performance, while the action space represented candidate next modules. Training was conducted over 1,000 episodes using an ϵ -greedy exploration strategy.

C. Baseline Models

Performance was compared against:

- Rule-based course generator
- Heuristic adaptive learning model

VII. RESULTS AND DISCUSSION

The proposed framework achieved:

- 34% improvement in learner engagement
- 27% reduction in course completion time
- 31% increase in personalization accuracy

These results demonstrate the effectiveness of reinforcement learning for adaptive and personalized course generation.

VIII. FUTURE WORK

Future enhancements include privacy-preserving decentralized learning, multimodal learner analytics, and instructor dashboards for predictive insights.

IX. CONCLUSION

This paper presented a reinforcement learning–based AI Course Generator for automated and personalized education. Experimental results indicate improved engagement and adaptability compared to static approaches. The proposed framework provides a scalable foundation for next-generation intelligent learning platforms.

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