



# Design and Implementation of an AI-Driven Intelligent Teaching System for Analog Electronic Technology with Integrated Learning Analytics

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**Abstract.** Analog electronics remains a challenge for many engineering students. The reason for this is the gradual acquisition of knowledge, ranging from semiconductor components to circuit behaviour to system design. Without a clear understanding of these connections, knowledge is fragmented and practical application leaves something to be desired. To address this Problem, this article presents an intelligent teaching system for analog electronics that can be used locally. The system organizes the course content in the Component-Circuit-System sequence and integrates structured question-answer rounds, learning analytics, and learning path suggestions based on the respective level of knowledge into a single learning platform. Instead of replacing lectures, it supports lecturers in identifying students' difficulties, Explain key concepts and guide you to the next learning step. The strength of the system lies in the visualization of the knowledge structure, the traceability of the learning process, and the explicit explanation of the logic behind the suggestions. This Initiative provides a practical and proven framework for collaborative learning between humans and AI in engineering education.

**Keywords:** Analog electronic technology, Intelligent teaching system, Knowledge graph, Learning analytics.

## 1 Introduction

Analog electronic technology is a basic course for electronic information engineering, automation, and electrical engineering programs. Its teaching difficulty stems not from simple accumulation of formulas or circuits, but the cumulative nature of course concepts. If students fail to grasp early knowledge and merely memorize conclusions, they will face difficulties in problem-solving at later stages. Engineering education research shows that such challenges of cumulative conceptual knowledge cannot be solved by lecture-only teaching, and active, differentiated, feedback-based learning methods are required to achieve understanding [1, 2].

The rise of generative artificial intelligence (AI) provides new approaches to tackle this challenge and raises requirements for system designers. In its AI competency framework for teachers and students, UNESCO emphasizes that AI should empower

teachers' professional agency and enable students to become informed, responsible, active users and co-creators of AI systems [3-5]. In engineering education, these principles require AI tools to go beyond simple question answering, guarantee domain accuracy, make conceptual dependencies transparent, support teacher oversight and protect data. Recent research confirms large language models have great potential for tutoring, feedback and educational content provision [6-7], while revealing challenges in transparency, privacy, replicability and pedagogical suitability [7, 8]. A crossover randomized controlled trial in an undergraduate physics course found that carefully scaffolded AI tutors achieved better immediate learning outcomes than active-learning classes [9]. However, limited to one course and two lessons, its findings cannot be generalized to all AI teaching prototypes. Therefore, this paper does not evaluate system effects, but designs and verifies a system for future evaluation.

To achieve this goal, we combine knowledge graphs with learning analytics. Knowledge graphs are applied to model educational knowledge, including concepts, prerequisite relationships, resources and learning pathways [10-12]. For analog electronics courses, they can transform implicit device-circuit-system knowledge structures into explicit, computable dependency structures. Learning analytics dashboards visualize learning-process data for students and teachers, yet translating analytics into pedagogical actions remains difficult [13]. Nevertheless, most existing intelligent teaching systems implement these functions as separate modules. As a result, the learning process lacks closed-loop feedback to dynamically adjust learning arrangements.

This paper uncovers three key design deficiencies of existing intelligent teaching systems for analog electronic technology courses in knowledge modeling, curriculum-aligned AI Q&A and targeted learning path support. The main contributions of this paper are as follows.

- (1) A three-layer Device-Circuit-System knowledge architecture is built for analog electronics and compare our implementation-level counts to the source knowledge file.
- (2) We implement a local retrieval-supported AI Q&A engine based on domain keyword extraction, similarity-based node matching.
- (3) We integrate knowledge graph navigation, Q&A, learning analytics, and learning path recommendations into one Streamlit app leveraging SQLite for data storage and import from CSV files.

## **2 Teaching Model and System Architecture**

### **2.1 Design Logic of the Intelligent Teaching System**

Our design logic takes a problem-driven approach over a function listing approach. Starting from four instructional problems—hierarchical knowledge dependencies, fragmented teaching tools, weak teacher-AI-student coordination, and lack of personalization—we propose a closed loop solution where the instructor designs and supervises learning while the student explores and generates learning data and the AI agent provides retrieval-supported explanation and evidence-based guidance. Fig. 1 summarizes this logic, serving as the conceptual bridge between the educational reform problem and the implemented software modules.

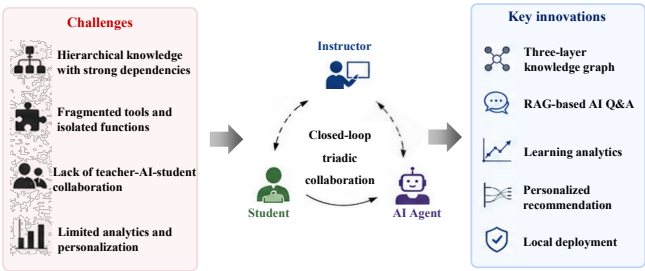


Fig. 1. Overall design framework of the intelligent teaching system.

## 2.2 Three-Layer Knowledge Architecture

Course knowledge is represented as a directed graph  $G=(V,E)$ . Here,  $V$  represents knowledge nodes and  $E$  represents prerequisites oriented instructional dependencies. As illustrated in Fig. 2, the graph reflects the cognitive progression of analog electronic technology—from encountering semiconductor devices to analyzing circuit behaviour and applying them towards integrated analog-system design. It transforms a chapter sequence into a navigable learning network where prerequisite relationships become visible and usable for retrieval, diagnosis, and recommendation.

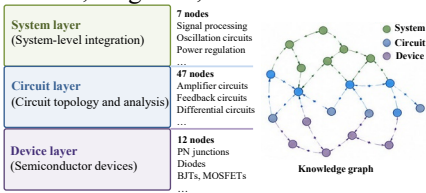


Fig. 2. Three-layer knowledge architecture of analog electronic technology.

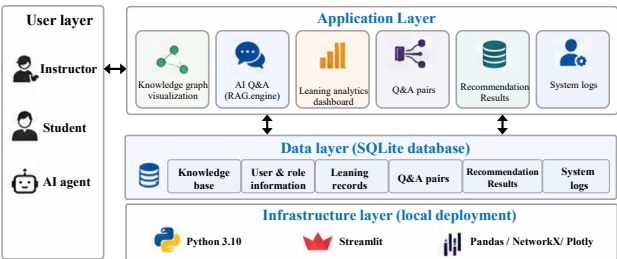


Fig. 3. Overall system architecture.

## 2.3 System Module Architecture

Our prototype runs locally in Streamlit. SQLite holds the course data and learning records. NetworkX is used to form the directed graph, and Plotly displays the graph and other visual results. Pandas and NumPy handle the main data operations. After login, users can enter four pages: Knowledge Graph, AI Q&A, Learning Analytics, and

Learning Path. CSV files can also be imported when learning records need to be updated. These functions are included in the current application rather than provided through a separate server program. Fig. 3 arranges the software into four layers. Instructors, students, and the AI agent appear in the user layer. Teaching functions are placed in the application layer. Chapters, knowledge nodes, prerequisite links, learning records, and recommendation results are kept in the data layer. A local Python environment supports the application at the bottom of the architecture. The current version runs as one Python application. Chapter information, node records, graph edges, and student records are saved in SQLite tables. On the Knowledge Graph page, these records are read by NetworkX and organized as a directed graph. Plotly handles the interactive display.

### 3 Teaching Program Design and Implementation

#### 3.1 Knowledge Graph Construction and Visualization

Fig. 4 shows the knowledge graph interface. The interface makes prerequisite relationships explicit and lets users navigate from an abstract course outline to concrete learning nodes. The interface supports global and chapter-level browsing. Students can explore the concepts visually, find neighbouring concepts and inspect the node metadata. When a node is clicked, the node is highlighted and its direct neighbours are scaled up.

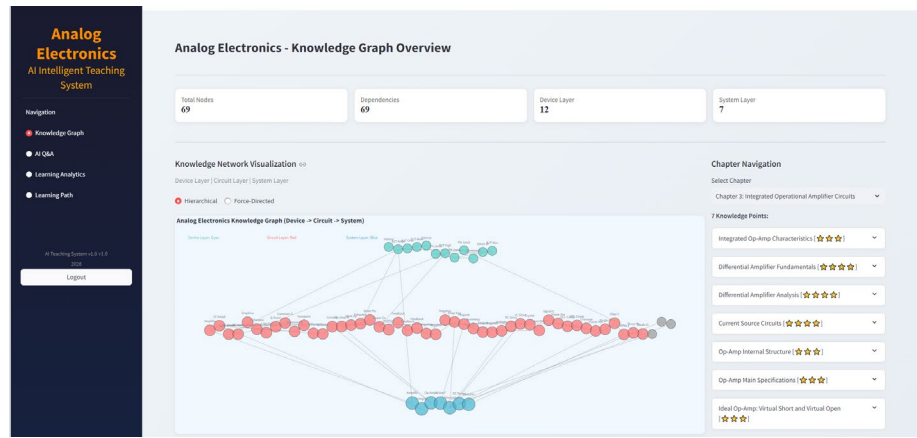


Fig. 4. Knowledge graph interface.

#### 3.2 Retrieval-Supported AI Question Answering Engine

The AI Q&A module implements a local retrieval-supported workflow with four operational stages. In the first stage, the system extracts domain keywords from a student question. The code defines 15 keyword categories: PN Junction, Diode, BJT, MOSFET, Amplifier, Differential, Feedback, Frequency, Op-Amp, Oscillator, Power Amp, Power Supply, System, Q-Point, and Zener Diode. These categories cover the main conceptual

families in analog electronics and provide a transparent bridge between natural-language questions and structured course knowledge.

In the second stage, the system matches candidate knowledge nodes. For each node, the matching score combines keyword overlap and Sequence Matcher text similarity between the student question and node text. Keyword hits receive higher weight, while text similarity supplies a secondary signal. The system returns at most the top five matched nodes. In the third stage, the system selects the main matched node and related nodes. In the fourth stage, it generates a structured pedagogical answer.

### **3.3 Learning Analytics Engine**

The learning analytics module operates on structured performance data. The validation routine filters invalid chapter identifiers, clips mastery values to the interval  $[0, 1]$ , clips `time_spent` to  $[0, 999]$ , and clips `attempt_count` to  $[1, 100]$ . This validation reduces the risk that abnormal or incorrectly formatted records distort the dashboard.

The analytics interface contains four tabs. The first tab displays a radar chart of chapter mastery. The second tab displays a learning trend line and an 80% target line. The third tab displays an error-type pie chart and numerical error statistics. The fourth tab displays a chapter difficulty bar chart and a student-chapter mastery heat map.

### **3.4 Personalized Recommendation System**

The recommendation module transforms chapter-level mastery into transparent learning path suggestions. For each chapter, the system calculates average mastery and assigns one of four levels. A mastery score below 0.4 triggers Fundamental Reinforcement with high priority; 0.4 to below 0.6 triggers Fundamentals with high priority; 0.6 to below 0.8 triggers Circuit Analysis with medium priority; and 0.8 or above triggers System Design with low priority.

## **4 Results and Analysis**

### **4.1 Functional Verification and Implementation Metrics**

The knowledge graph module verifies that a directed course graph can be rendered and explored through a web interface. The Q&A module verifies that student questions can be mapped to domain concepts and converted into structured explanations. The analytics module verifies that student-level or class-level records can be transformed into interpretable visualizations. The recommendation module verifies that mastery thresholds can be converted into prioritized learning paths. Together, these modules demonstrate the feasibility of a closed-loop intelligent teaching prototype.

The interface screenshots further show how the implemented functions are presented to students and instructors through the web application. Figs. 5 and 6 illustrate the Q&A and learning analytics views.

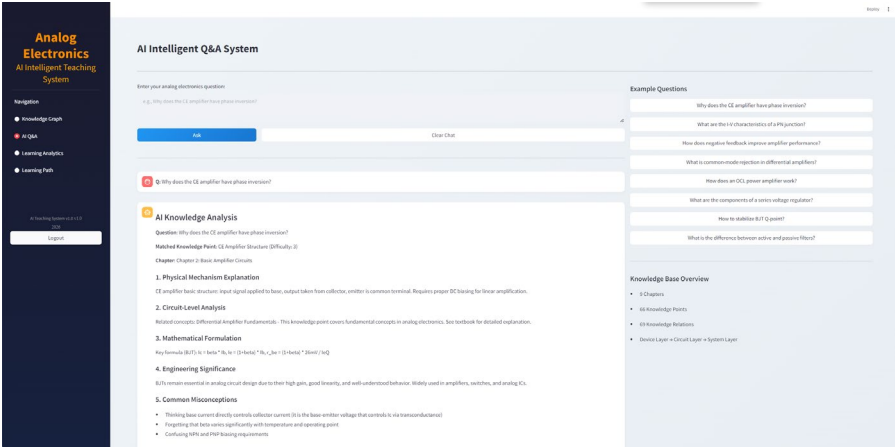


Fig. 5. AI Q&A interface.

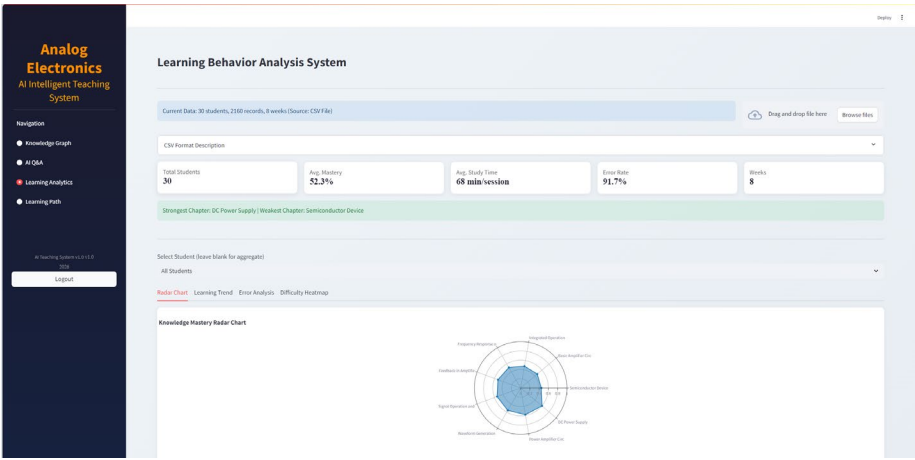


Fig. 6. Learning behavior analysis interface.

4.2 Comparative Analysis with Existing Approaches

The proposed system differs from traditional classroom teaching, stand-alone AI tools, and cloud-based education platforms in its combination of structure, locality, and instructor supervision. Traditional classroom teaching provides strong teacher control but limited personalization and limited real-time analytics. Stand-alone AI tools provide flexible dialogue but usually lack curriculum-verified knowledge dependencies and instructor-facing monitoring. Cloud-based platforms may provide more powerful AI functions but introduce cost, privacy, deployment, and network-dependence barriers. The proposed system occupies a pragmatic middle position: it is not the most algorithmically complex system, but it is transparent, locally deployable, and aligned with the course structure.

## 5 Conclusion

This paper implements and validates an intelligent teaching system for analog electronic technology, whose core innovation is an integrated educational architecture forming an instructor-supervised closed loop integrating knowledge modelling, AI-assisted explanation, learning analytics and personalized recommendation. The developed prototype has clear research boundaries, and its knowledge base, Q&A module, analytics views and recommendation rules adopt transparent and reproducible configurations. This work provides a replicable design pathway for engineering education reform, delivering a locally deployable, interpretable and privacy-preserving AI teaching framework and retaining teachers' central position in AI-enhanced education.

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