

Article

Smart Course Construction for Signal Analysis and Processing: A Three-Dimensional Ecological Framework Based on Knowledge Graphs and AI Tutoring

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Abstract: Digital transformation in higher education relies heavily on smart course development as its core practical carrier. Many existing smart course practices for Signal Analysis and Processing merely integrate standalone technical tools while overlooking the holistic integration of curriculum elements and the in-depth reconstruction of teaching processes. Drawing on the inherent pedagogical characteristics of this engineering course, this paper proposes a smart course development framework anchored in knowledge graphs, empowered by AI teaching assistants for interactive tutoring, and sustained by data-driven teaching diagnostic and feedback mechanisms. This study argues that smart course construction is far more than a simple upgrade of technical equipment; it represents a comprehensive reshaping of the ecosystem of knowledge organization, instructional interaction and formative assessment within curriculum design. The practical value of such courses does not hinge on the richness of AI functions; instead, it depends on how deeply intelligent technologies are embedded into disciplinary teaching logic.

Keywords: smart course; Signal Analysis and Processing; knowledge graph; AI teaching assistant

1. Introduction

Signal Analysis and Processing serves as a compulsory foundational course for electronic information majors, covering time-domain analysis, frequency-domain transformation, system function modelling and filter design. The subject is characterized by abstract concepts, intensive mathematical derivations, and tight links between theoretical formulas and engineering applications. For a long time, classroom delivery has been constrained by three prominent teaching bottlenecks. First, abstract concepts including convolution and Fourier transforms cannot be easily visualized in conventional lectures. Students may follow algebraic calculations step by step, yet struggle to interpret the underlying physical mechanisms. Second, mathematical derivations are often isolated from engineering intuition: even after mastering transform properties, students still lack viable strategies to tackle real-world signal processing problems. Third, large-group teaching cannot accommodate diversified learning demands among students at different proficiency levels, a challenge echoed in recent practice-based studies of signal-related courses [1,2]. As a result, learning deficits may remain undetected until final assessments. Advances in smart education bring new possibilities for addressing these long-standing teaching challenges.

Nevertheless, many universities reduce smart course construction to knowledge graph construction, AI chatbot deployment or smart classroom renovation. Such practices ignore how technical modules should align with the intrinsic disciplinary logic of course instruction. Teachers tend to focus on adopting new digital tools rather than redesigning teaching activities and assessment schemes, creating a disconnect between pedagogical

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ideas and actual learning gains [3]. Smart course development should shift away from discussing "available technologies" and return to the core question: how digital technologies can genuinely facilitate students' learning.

In recent years, global research on smart education and intelligent tutoring systems has evolved along two mainstream strands. The first focuses on general educational ecology, exploring online–offline blended models, learner behavior profiling, and data-driven formative evaluation, which provides macro-level theoretical support for digital teaching reform [4]. The second concentrates on disciplinary intelligent teaching, applying knowledge visualization, simulation tools and artificial intelligence to STEM (Science, Technology, Engineering and Mathematics) courses with strong logical and mathematical attributes [5,6]. However, most existing frameworks remain universal and tool-oriented, lacking systematic cognitive adaptation for highly abstract, mathematically intensive engineering courses such as Signal Analysis and Processing. Domestic smart teaching practices for signal-related courses also tend to accumulate fragmented digital resources rather than reconstruct coherent cognitive paths and interactive tutoring logic, resulting in limited pedagogical improvement [7,8]. This research gap exists both internationally and domestically. Few studies have established a discipline-specific smart teaching ecosystem integrating knowledge reconstruction, scaffolded AI interaction, and closed-loop diagnostic intervention.

Against this background, this study takes Signal Analysis and Processing - a theoretically heavy and conceptually abstract course - as the research object and explores a replicable, practical pathway for smart curriculum instructional reconstruction. This paper constructs a three-dimensional ecological smart teaching framework tailored to the cognitive characteristics of signal courses and puts forward corresponding targeted construction strategies. The findings are expected to provide actionable references for the smart transformation of analogous mathematically intensive engineering courses. The rest of this paper is organized as follows. Section 2 establishes an ecological perspective to reinterpret smart courses, departing from the traditional tool-oriented view. Section 3 identifies discipline-specific teaching obstacles requiring targeted technical support. Section 4 elaborates three mutually connected construction strategies, and Section 5 summarizes insights and actionable recommendations.

2. Theoretical Foundation: A Three-Dimensional Ecological View of Smart Courses

To clearly define smart courses, it is necessary to distinguish them from traditional online courses and blended learning courses. Simply adding AI question-and-answer (Q&A) functions or enriching video resources only yields upgraded digital resources, rather than authentic smart courses.

Rooted in cognitive load theory and learning ecosystem theory, the core mission of smart education is to provide adaptive, learner-centered support and developmental experiences, cultivating learners capable of autonomous learning, collaborative work, critical reasoning and innovative thinking. Accordingly, smart courses are not designed merely to improve teaching efficiency; their primary goal is to foster deep learning. From this perspective, smart teaching systems emphasize dynamic coordination and mutual reinforcement of multiple teaching elements, rather than isolated technical superposition. This study further decomposes smart course construction into three interdependent dimensions: knowledge organization, instructional interaction, and assessment feedback.

On the dimension of knowledge organization, smart courses depart from the linear chapter-based textbook structure and adopt networked representation to visualize conceptual relationships. Traditional linear textbooks fail to reflect the highly interconnected knowledge system of Signal Analysis and Processing. Classroom observations reveal that many students fail to recognize that Fourier, Laplace and Z-transforms originate from the same mathematical idea extended across different domains. A knowledge graph, therefore, renders these implicit conceptual connections explicit, enabling learners to build coherent cognitive frameworks rather than memorizing isolated formulas [5].

On the dimension of instructional interaction, smart courses transform the one-way model of "teacher lecture, student reception" into tripartite collaboration among teachers, machines and learners. AI teaching assistants do not replace instructors in answering questions; they provide on-demand scaffolded cognitive support beyond in-class teaching [4,6]. Their core value lies not in delivering ready-made answers, but in guiding learners through layered questioning to move from mechanical algebraic calculation toward physical understanding.

On the dimension of assessment and feedback, smart courses prioritize ongoing diagnostic evaluation rather than end-of-term summative tests. Learning barriers in Signal Analysis and Processing accumulate progressively: weak mastery of frequency-domain analysis will hinder subsequent learning of filter design. Learning behavior data captured by the knowledge graph system helps instructors identify individual knowledge gaps and deliver timely intervention early [5].

The overall theoretical structure and internal logical relationships of the three-dimensional ecological smart course framework are illustrated in Figure 1.

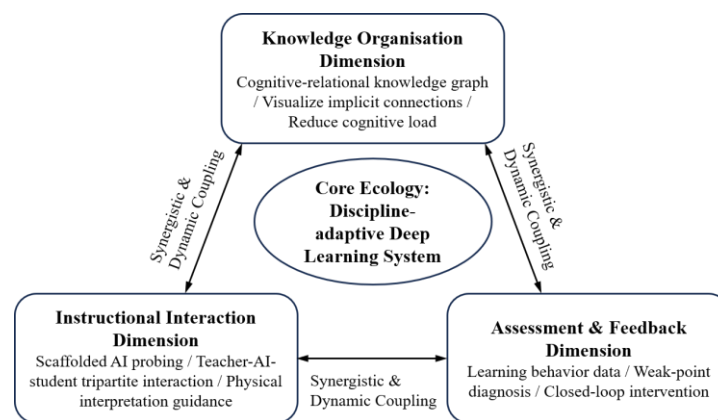


Figure 1. Three-Dimensional Ecological Framework of Discipline-Specific Smart Courses

3. Teaching Pain Points and Technological Adaptation

High-quality instructional design starts with accurate identification of teaching difficulties. The three challenges outlined in the introduction - abstract concepts, separation between mathematical derivation and engineering intuition, and insufficient personalized support in large-class teaching - are translated into three discipline-specific pain points. The first two pain points are analyzed in this section because both require technologies adapted to the cognitive nature of the discipline. The third pain point, personalization in large classes, is fundamentally a diagnosis-and-intervention problem rather than a representation problem, so it is addressed via the data-driven closed-loop mechanism described in Section 4.3. In other words, smart course construction for this subject cannot directly copy generic templates; technologies must be customized to match discipline-specific teaching difficulties.

3.1. Pain Point 1: High Cognitive Barriers to Abstract Concepts

Core concepts such as convolution, Fourier transforms and system functions rely heavily on symbolic operations and mathematical derivation. Three years of classroom observations reveal that students' most frequent confusion lies not in algebraic computation, but in the physical essence of convolution: why signals are flipped, what time shift represents, and what integration operations signify. Prior literature indicates that converting the flip, shift and integration operations of convolution into interactive dynamic visualization can effectively reduce cognitive load [7]. Therefore, AI teaching assistants should go beyond simple Q&A functions and translate mathematical expressions into interpretable physical descriptions.

3.2. Pain Point 2: Disconnect between Mathematical Derivation and Engineering Intuition

Even after mastering the algebraic steps of transform derivations, students often struggle to map these operations onto engineering intuition and real-world applications. For instance, learners can successfully derive filter transfer functions yet find it difficult to interpret their practical roles in communication systems or image processing. Formal derivation and physical insight thus remain decoupled when instruction emphasizes symbolic manipulation at the expense of engineering context. Virtual simulation and code-generation tools are expected to help learners translate theoretical knowledge into implementable systems at low cost, bridging the so-called "last mile" between theory and engineering practice.

3.3. Pain Point 3: Insufficient Personalized Support in Large-Class Teaching

Large-group instruction can rarely accommodate students at different proficiency levels, and this challenge is compounded in a course where knowledge accumulates cumulatively. Learners who fall behind in earlier topics may struggle with subsequent material, yet their learning deficits often remain undetected until final assessments. Unlike the first two pain points, which call for adapted technological representation, this one is fundamentally a diagnosis-and-intervention problem. It is therefore addressed through the data-driven closed-loop mechanism presented in Section 4.3, which leverages learning behavior data to locate individual knowledge gaps and deliver timely targeted intervention.

4. A Practical Framework: Three Core Strategies

Based on the course characteristics and identified teaching obstacles, smart course construction for Signal Analysis and Processing can be organized around three interrelated strategies. These strategies correspond to the three-layer ecological framework described in Section 2: knowledge organization, instructional interaction and assessment feedback.

This matching is not coincidental. The learning barriers of this course are cumulative and mathematically intensive. The greatest instructional leverage lies precisely in three functions: coherent knowledge representation, a guided reasoning interface, and early diagnosis, which are exactly what these strategies achieve. The three strategies therefore operate as mutually reinforcing components rather than isolated technical add-ons. The mutually reinforcing three-core construction framework is presented in Figure 2. As shown in Figure 2, these three strategies target the identified teaching pain points of Signal Analysis and Processing. Collectively, they contribute to the ecological reconstruction of smart courses and genuine teaching effectiveness, supporting deep learning, cultivation of engineering competence, and personalized teaching for large engineering classes.

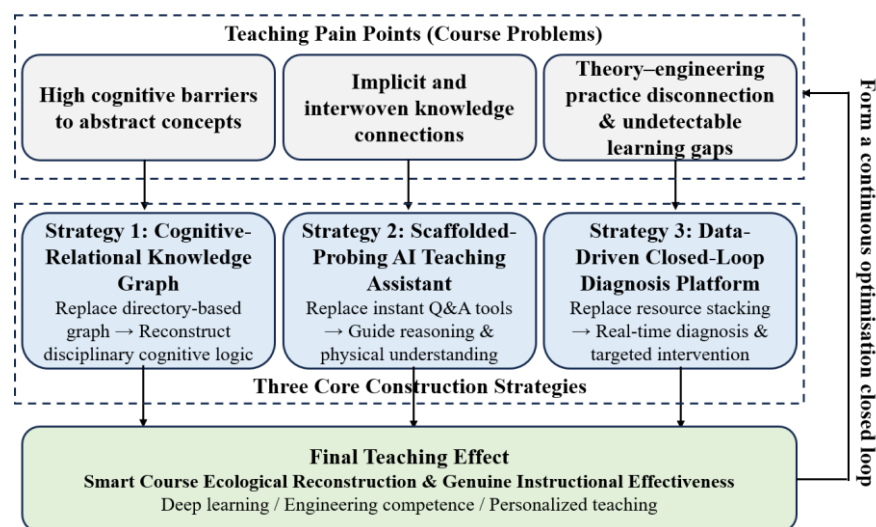


Figure 2. Three-Core Practical Construction Strategy Framework for the Smart Course

4.1. Building a "Cognitive-Relational" Knowledge Graph Rather Than a "Directory" Graph

Knowledge connections in this course are often implicit and interwoven and scattered across separate textbook chapters, making it difficult for students to perceive the logical links among transform families and dual relationships [5]. Many existing knowledge graphs act as visualized tables of contents, where nodes are only connected through hierarchical inclusion relationships. For this course, the graph should highlight three discipline-specific relationship categories: (1) prerequisite-succession chains; for instance, continuous-time Fourier transform forms the cognitive foundation for discrete-time Fourier transform; (2) time-frequency duality, such as time-domain convolution corresponding to frequency-domain multiplication; (3) continuous-discrete extension paths, such as the generalization from Fourier to Laplace transforms. Relevant practices from Beijing Information Science and Technology University suggest that such relation-rich graphs help learners identify learning obstacles and cognitive discontinuities [7]. In this sense, the quality of a knowledge graph should be measured not by the quantity of nodes, but by the robustness of cognitive connections.

4.2. Designing a "Scaffolded-Probing" AI Teaching Assistant Rather Than an "Instant-Answer" Q&A Tool

Conventional AI assistants adopt a simple Q&A paradigm, assuming learners already know what questions to raise. In this course, however, learners often cannot identify their own knowledge deficits. A well-designed AI teaching assistant should adopt scaffolded probing: starting with motivational questions about conceptual origins, explaining physical interpretations of formula steps, and extending to practical scenarios where mathematical properties apply. Within this paradigm, AI shifts from an answer provider to a thinking facilitator, whose pedagogical value exceeds ordinary Q&A tools [4,6]. Beyond text dialogue, the assistant can trigger lightweight virtual simulation widgets. For example, adjusting the cutoff frequency of a low-pass filter and visualizing filtered spectra in real time bridges the theory-to-practice gap described in Section 3.2 within a single interaction.

4.3. Forming a "Data-Driven Closed-Loop Diagnosis" Rather Than a "Resource-Stacking" Platform

This strategy directly targets the insufficient personalized support in large-class teaching identified as Pain Point 3. Smart learning platforms collect abundant learning behavior data, including video viewing duration, quiz accuracy and click frequency of knowledge nodes. If these datasets are only used to generate descriptive learning reports, their educational potential remains under-exploited. Data-driven teaching follows a closed-loop workflow: diagnosis of weak knowledge points, delivery of targeted micro-lectures or variant exercises, and verification of intervention effectiveness using subsequent learning performance. Research on multimodal knowledge graphs and learner profiling provides feasible approaches to implementing such diagnostic mechanisms [5]. For this course, special attention should be paid to mastery of frequency-domain analysis and filter design, because knowledge gaps at these nodes will trigger cascading difficulties in subsequent learning.

5. Reflections and Suggestions

Smart course construction has entered an in-depth development phase after the initial wave of conceptual hype. Featuring profound theoretical content and high abstraction, Signal Analysis and Processing represents one of the most challenging scenarios for smart teaching, and also acts as a litmus test for the philosophy guiding smart course development.

One pitfall to avoid is a "technology feature race": competing over the visual aesthetics of knowledge graphs, the number of AI functions, or the richness of dashboards. Existing research shows that instructional philosophies affect learning outcomes only indirectly; technologies improve learning outcomes only when embedded within

instructional design [3]. The underlying logic is that teaching problems drive technology selection, rather than technical features driving instructional redesign. Essentially, the three interrelated strategies shown in Figure 2 aim to realize ecological reconstruction of smart courses and produce authentic teaching outcomes, including promoting deep learning, cultivating students' engineering competence, and enabling personalized teaching in large STEM classes.

Another issue worthy of deep reflection: when AI can explain the physical meaning of convolution and generate sample code for filter design, what core value remains for classroom instructors? AI excels at explanation and response; teachers excel at inspiration and intellectual enlightenment. AI can provide correct answers; teachers help students understand why a research question is worth exploring. When teaching Fourier transforms or the sampling theorem, the greatest value lies not merely in "understanding formulas", but in enabling students to perceive the power and elegance of theories. This type of intellectual experience cannot be replaced by artificial intelligence.

We therefore propose constructing the smart course of Signal Analysis and Processing around three interconnected layers: a knowledge graph layer externalizing cognitive logic, an AI assistant layer for scaffolded dialogue, and a data diagnosis layer implementing closed-loop targeted intervention. These three layers are intended to work synergistically rather than being mechanically stacked. Only with such synergy can smart courses move beyond technical demonstration and achieve genuine teaching effectiveness.

Several limitations of this study should be acknowledged. The proposed framework is developed within China's higher education context and based on a single disciplinary case; its transferability to other STEM courses or different educational systems awaits empirical validation. Future research may adopt controlled quasi-experiments to compare learning outcomes between students receiving the proposed smart course intervention and those taught via conventional approaches, alongside longitudinal studies tracking the evolution of AI assistant dialogue patterns. Furthermore, with continuous advances in large language models, the boundary between content explainable by AI and content requiring human teachers' inspiration will continue to shift, so the division of roles proposed in this paper requires ongoing reconsideration.

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