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DESIGNING AN INTELLIGENT LEARNING ENVIRONMENT FOR TEACHING SYSTEMS AND SIGNAL PROCESSING

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Abstract
Systems and signal processing courses combine mathematical abstraction, algorithmic reasoning, simulation, and engineering judgment, yet conventional learning environments often present these elements as separate activities. This article proposes an intelligent learning environment (ILE) that unifies adaptive content delivery, learner modeling, intelligent tutoring, simulation-based experimentation, learning analytics, and instructor oversight for teaching signals, systems, and digital signal processing. The study follows a design-science methodology. First, pedagogical and technical requirements were derived from recent research on artificial intelligence in education, intelligent tutoring systems, learning analytics, virtual laboratories, and contemporary signal-processing pedagogy. Second, the requirements were translated into a closed-loop architecture consisting of input and evidence sources, a dynamic learner model, a pedagogical decision engine, a domain and simulation layer, and a human-centered analytics and feedback layer. Third, the architecture was examined through task walkthroughs and synthetic learner scenarios rather than human-subject experimentation. The resulting design supports diagnosis of prerequisite knowledge, individualized sequencing, adaptive task difficulty, automated hints, project recommendations, simulation and virtual laboratory activities, reflection prompts, and instructor override.

Keywords: Intelligent learning environment; signal processing education; signals and systems; adaptive learning; intelligent tutoring system; learning analytics; virtual laboratory; engineering education

Introduction

Signals and systems and digital signal processing are foundational subjects in electrical engineering, computer engineering, telecommunications, automation, data science, and related programs. Their educational difficulty is not caused by a single topic but by the need to coordinate several forms of reasoning at once: students must move between continuous- and discrete-time representations, interpret transforms and spectra, understand system properties, connect equations to visual behavior, write code, and evaluate whether an engineering result is meaningful. Contemporary signal-processing education therefore increasingly emphasizes design, experimentation, simulation, and authentic applications rather than lecture-only

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delivery. Aboutanios et al. (2021), for example, describe a design-centered signal-processing curriculum in which frequent and diverse design activities are used to connect theory with practice.

Technology-rich instruction alone, however, does not guarantee individualized learning. A typical learning management system can distribute the same notes, examples, and assignments to every student even when learners differ greatly in prerequisite knowledge, misconceptions, pace, mathematical confidence, and programming skill. Intelligent educational technologies aim to address this limitation by using learner evidence to personalize the learning sequence, feedback, support, and difficulty. Reviews of artificial intelligence in education show strong growth in personalized learning, intelligent tutoring, learning analytics, and adaptive environments, while also stressing the need for safe implementation, human control, and pedagogical alignment (Alfredo et al., 2024; Mustafa et al., 2024; Kerimbayev et al., 2025). In engineering education specifically, AI-driven intelligent tutoring systems are increasingly discussed in terms of personalization, feedback, and student monitoring (Rodrigues et al., 2025).

The pedagogical characteristics of signal processing make it particularly suitable for an intelligent learning environment. Many learning tasks generate observable evidence: a student can classify a signal, compute convolution, interpret an impulse response, identify aliasing, design a filter, inspect a frequency response, debug a numerical script, or justify the selection of a sampling rate. These actions can be evaluated not only by a final answer but also by intermediate steps, parameter choices, simulation outputs, error patterns, time-on-task, and requests for hints. Virtual and remote laboratories already demonstrate that signal-processing concepts can be explored through web-based and simulation-supported experimentation, and recent virtual-laboratory implementations explicitly emphasize visualization, spectral estimation, filtering, and statistical signal analysis. Python- and Jupyter-based DSP instruction further illustrates how theoretical explanation, code, and graphical output can be integrated in a single learning workflow (Zúñiga-López & Avilés-Cruz, 2020).

Despite these developments, a gap remains between isolated educational technologies and a coherent architecture designed specifically for Systems and Signal Processing. Existing tools may provide a virtual laboratory, an analytics dashboard, an AI tutor, or adaptive exercises, but the pedagogical value depends on how these components exchange evidence and how the system keeps the instructor in control. Human-centered learning analytics research warns that excluding learners and teachers from system design can weaken trust and alignment, while student-facing dashboards are increasingly expected to support learning decisions rather than merely display activity counts (Alfredo et al., 2024; Paulsen & Lindsay, 2024). Therefore, the central problem addressed in this study is how to design an intelligent learning environment in which adaptation, simulation, analytics, assessment, and teacher decision-making operate as a single closed learning loop. The study is guided by three research questions: (RQ1) What pedagogical and technical requirements should an intelligent learning environment satisfy for university-level Systems and Signal Processing? (RQ2) How can learner modeling, pedagogical decision-making, domain knowledge, simulation, and analytics be integrated into

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a coherent architecture? (RQ3) How can the proposed architecture operationalize adaptive learning without presenting synthetic design demonstrations as empirical evidence of effectiveness?

Materials and Methods

A design-science research approach was used because the primary objective was to construct and justify an educational artifact rather than estimate a treatment effect. The process comprised four stages: problem analysis, requirement synthesis, architecture design, and scenario-based validation. The literature base focused on five intersecting areas: signal-processing pedagogy, intelligent tutoring systems, adaptive and personalized learning, learning analytics, and virtual/simulation laboratories. Recent systematic reviews and domain-specific studies were prioritized to ensure that the design reflects current educational technology practice. The resulting requirements were then translated into functional modules and explicit information flows.

Table 1. Pedagogical and technical requirements of the proposed intelligent learning environment.

Requirement	**Design purpose**	**Signal-processing example**
R1. Diagnostic modeling	Estimate prerequisite and current mastery before sequencing content.	Fourier prerequisites, complex numbers, convolution, LTI concepts, sampling.
R2. Adaptive sequencing	Choose the next concept, representation, or task based on evidence.	Move from time-domain intuition to transform-domain analysis when prerequisite mastery is adequate.
R3. Intelligent feedback	Provide hints that target the learner's error rather than reveal the answer.	Detect sign errors in convolution, sampling misconceptions, unstable filter parameters, or incorrect FFT interpretation.
R4. Simulation integration	Connect equations to visible and executable system behavior.	Waveforms, spectra, pole-zero plots, impulse/step responses, filter outputs.
R5. Authentic problem solving	Recommend project and inquiry tasks that require engineering judgment.	Noise reduction, system identification, spectral analysis, biomedical/audio signal processing.

No human participants, grades, or institutional learning records were used. Consequently, the study does not report empirical learning gains, statistical significance, or causal effects. The only numeric trajectories shown later are synthetic scenarios created to test whether the design logic can express different support paths. This distinction is important because a conceptual system architecture should be empirically evaluated in a subsequent implementation study before claims about effectiveness are made.

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Requirements were derived by mapping recurring educational needs in the literature to the distinctive learning activities of signals and systems courses. The design assumes that intellectual progress in the course is demonstrated through explanation, modeling, transformation, experimentation, interpretation, and justified engineering decisions. Therefore, adaptation is not restricted to choosing an easier or harder quiz item; it also includes selecting representations, simulations, hints, projects, and reflective prompts appropriate to a learner's state. The architecture was organized as a closed-loop system with five functional layers. Inputs and learning evidence feed a learner model; the learner model informs a pedagogical engine; the pedagogical engine selects resources and activities from the domain and simulation layer; learner interaction with those activities produces new evidence; and analytics support both automated adaptation and instructor decision-making. Figure 1 summarizes this information flow.

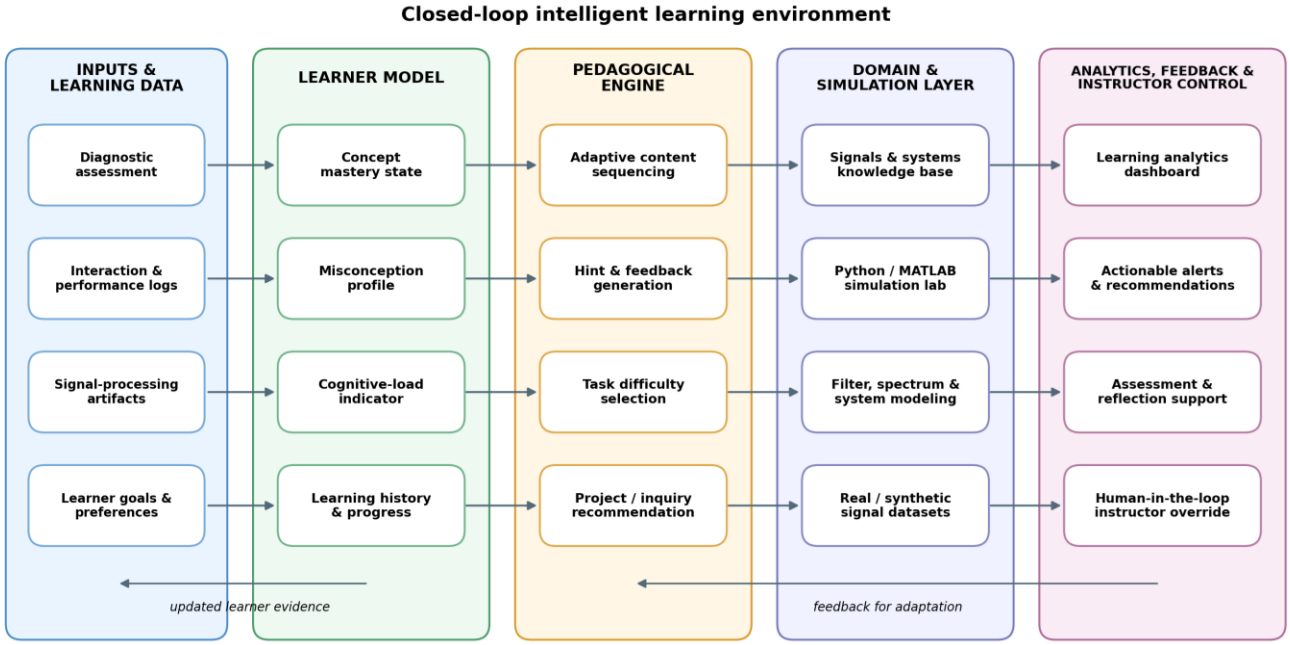


Fig 1. Closed-loop architecture of the proposed intelligent learning environment for Systems and Signal Processing.

The learner model stores concept-level mastery estimates and complementary indicators rather than a single overall score. A concept vector can include mastery values for signal classification, convolution, LTI system properties, Fourier analysis, sampling, z-transform, digital filter design, and spectral analysis. Additional state variables record repeated misconceptions, recent response time, hint use, confidence or self-explanation quality, and the learner's project history. This richer representation helps prevent over-adaptation based on one incorrect answer.

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Table 2. Example transparent adaptation rules. Thresholds are illustrative design parameters, not validated cut-offs.

Observed state	Illustrative trigger	System response
Low prerequisite readiness	P < 0.50	Assign prerequisite micro-lesson and worked example before the target task.
Persistent misconception	E >= 0.60 after two attempts	Change representation; provide conceptual hint and targeted simulation.
High hint dependence	H >= 0.50 with moderate mastery	Reduce answer-revealing hints; request self-explanation before the next hint.
Stable mastery	M >= 0.80 across multiple evidences	Advance to open-ended design or project task.
Fast correct performance	High accuracy with short solution time	Offer enrichment path, parameter sensitivity study, or comparative method task.
Instructor concern	Teacher flag or dashboard alert	Pause automatic progression and prioritize instructor-selected intervention.

For design purposes, the pedagogical engine can be expressed as a rule-and-score mechanism. Let M_i denote estimated mastery of concept i on a 0-1 scale, E_i a misconception severity indicator, H_i recent hint dependence, and P_i prerequisite readiness. A task readiness score can be represented as $R_i = 0.50M_i + 0.25P_i - 0.15E_i - 0.10H_i$. The coefficients are not claimed as empirically optimized parameters; they simply demonstrate how multiple evidence sources can be combined. In a deployed system, parameters should be calibrated using real learner data and validated against educational outcomes.

A six-stage adaptive cycle was defined to test whether the architecture could support a complete learning episode. The cycle begins with diagnosis and activity selection, continues through practice and evidence collection, then adapts the next instructional action and ends with learner reflection. The updated evidence returns to the learner model, creating a continuous feedback loop. This workflow is shown in Figure 2.

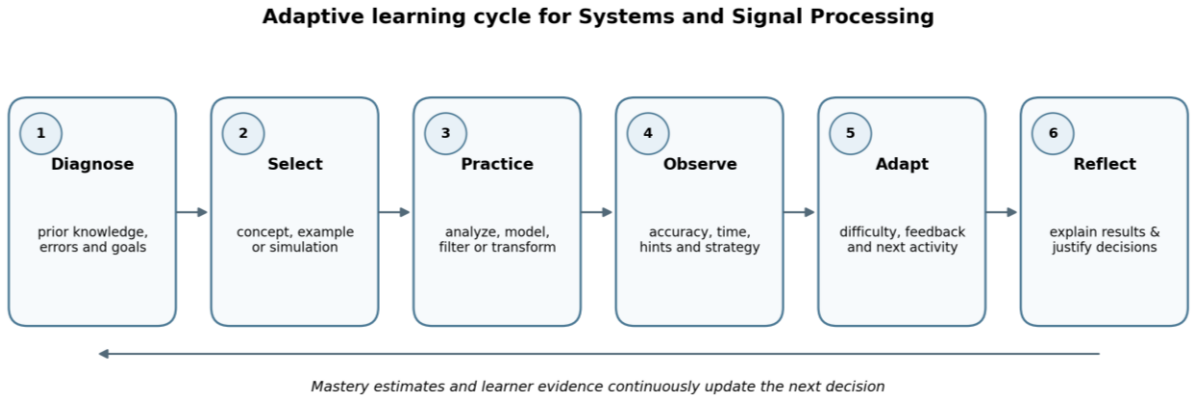


Fig 2. Adaptive learning cycle supported by the proposed environment.

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Scenario-based validation used three synthetic learner profiles. Profile A began with weak prerequisite mastery and therefore received worked examples, low-complexity simulations, and frequent conceptual prompts. Profile B began at an intermediate level and received a balanced path of guided analysis and progressively open tasks. Profile C began with stronger mastery and was directed toward comparative design, parameter sensitivity, and project-oriented enrichment. The scenarios were manually checked against the requirements in Table 1 to determine whether the architecture could represent the intended decisions without contradictions.

Results

The main design result is the five-layer closed-loop architecture shown in Figure 1. The architecture makes three separations that are pedagogically important. First, learner evidence is separated from pedagogical decisions: raw interaction logs do not directly determine instruction until they are interpreted in the learner model. Second, the pedagogical engine is separated from the domain layer: the system can choose among multiple representations and activities without embedding pedagogical policy inside each simulation. Third, automated adaptation is separated from instructor control: analytics and recommendations are visible to the teacher, who can override a sequence when classroom context or professional judgment indicates a different action.

The domain and simulation layer is intentionally central to the signal-processing context. Unlike a generic adaptive quiz system, the proposed environment can invoke executable learning objects such as a convolution visualizer, sampling and aliasing simulation, FFT and spectrum explorer, pole-zero tool, filter design sandbox, or system-response notebook. Each activity returns structured evidence, including parameter choices and interpretation questions, so that mathematical results are linked to conceptual reasoning.

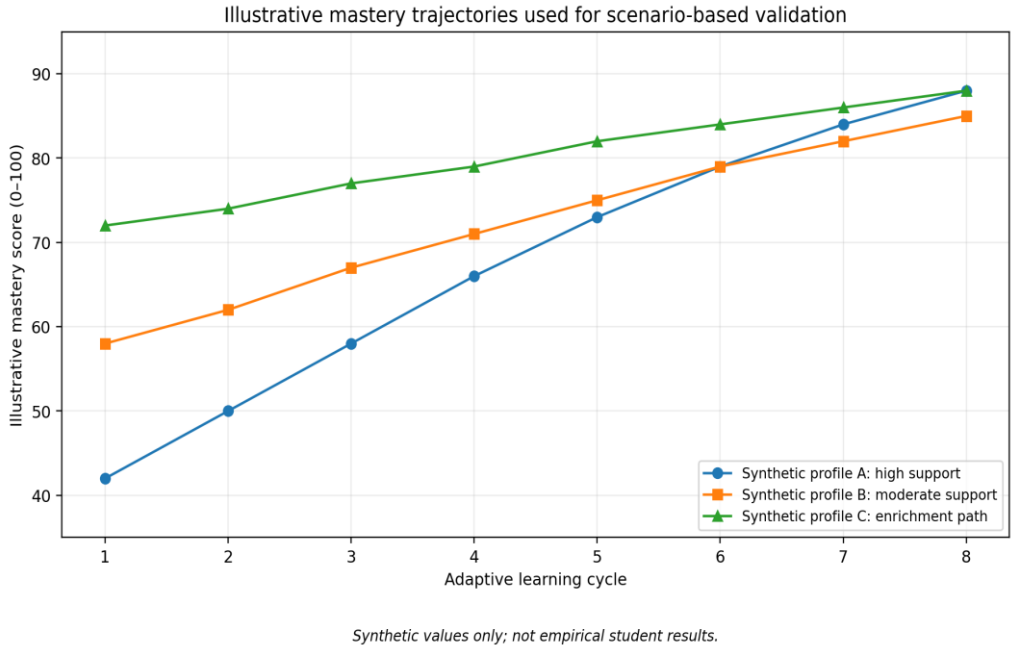


Fig 3. Synthetic learner trajectories used only for scenario-based validation of the adaptive logic

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The synthetic scenarios confirmed that the architecture can maintain different instructional trajectories without changing the underlying course outcomes. Profile A receives more scaffolding early in the sequence, while Profile C receives enrichment rather than repetitive remediation. Figure 3 visualizes illustrative mastery values across eight adaptive cycles. The curves do not represent observed student performance; they are design-test values used to verify that the architecture can depict converging progress under different support intensities.

Table 3. Scenario profiles used to inspect whether the system can produce differentiated learning paths

Synthetic profile	Initial illustrative mastery	Early support	Typical activity	Progression rule
Profile A: high support	42	Worked examples + visualization	Guided convolution and sampling simulations	Move to standard path after sustained mastery evidence.
Profile B: moderate support	58	Guided practice + selective hints	FFT interpretation and filter tasks	Increase task openness as hint dependence decreases.
Profile C: enrichment	72	Minimal scaffolding	Comparative filter design and open project	Prioritize design trade-offs, justification, and project autonomy.

Because the present study is architectural, the final result is also an evaluation plan for the next implementation phase. A future quasi-experimental or randomized study should compare the intelligent environment with a conventional digital course while measuring both conceptual learning and process variables. Evaluation should not rely only on final test scores; it should also examine transfer, quality of engineering decisions, learner agency, instructor workload, transparency, and the usefulness of feedback.

Discussion

The proposed environment extends the idea of technology-enhanced signal-processing education by making adaptation a property of the entire learning loop rather than a feature attached to a quiz. This is consistent with contemporary DSP pedagogy, which increasingly values design, projects, laboratories, open-source computational tools, and practical interpretation (Aboutanios et al., 2021; Bordallo López, 2025; Alqudah & Sababha, 2025). It also aligns with research on intelligent tutoring systems that emphasizes personalization and feedback, and with learning-analytics research that calls for actionable information instead of passive dashboards (Paulsen & Lindsay, 2024; Rodrigues et al., 2025).

A key design choice is the use of signal-processing artifacts as learner evidence. In many generic online courses, analytics rely heavily on clicks, page views, and completion counts. For a technical subject, richer evidence is available. A filter design can be inspected for stability and specification compliance; a spectrum interpretation can reveal misconceptions about

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leakage or aliasing; a system model can be tested against measured data; and a code-based solution can be compared with the student's written justification. Such evidence offers a more direct connection between analytics and disciplinary competence. Ouyang and Zhang (2024) note the importance of connecting AI-driven analytics with learning theory and using analytics to support actionable instructional interventions. The present architecture operationalizes that principle by routing evidence through a learner model and pedagogical engine before recommendations are made.

Another important feature is the human-in-the-loop structure. AI-supported education can increase scalability, but over-automation may reduce teacher agency or encourage students to accept generated guidance without sufficient reasoning. Human-centered learning analytics research stresses the importance of control, safety, reliability, and trust (Alfredo et al., 2024). In the proposed model, the instructor can inspect why a learner was assigned remediation, modify the task path, suspend an automated recommendation, or intentionally expose a student to productive difficulty. This design also makes the environment more suitable for research because instructor overrides themselves become analyzable evidence about where the automated model fails or requires refinement.

The architecture is compatible with existing computational ecosystems. The simulation layer could be implemented through Python/Jupyter, MATLAB or Octave notebooks, web-based visualization libraries, or remote laboratory interfaces. Prior work has demonstrated that Jupyter notebooks can integrate theory, code, and graphical results in DSP courses (Zúñiga-López & Avilés-Cruz, 2020), while virtual DSP laboratories have long been used to overcome limitations of equipment, place, and time. The intelligent layer proposed here does not replace these environments; rather, it coordinates when and why a learner should use a particular simulation, experiment, or project.

The study has several limitations. First, the architecture has not yet been evaluated with real students, so no claims can be made about learning effectiveness or effect size. Second, the illustrative adaptation rules and weights were selected for transparency rather than optimized from data. Third, automated interpretation of open-ended engineering reasoning is technically difficult and may require a combination of rule-based checks, numerical verification, natural-language processing, and teacher review. Fourth, privacy and fairness require careful treatment because learner models can become sensitive profiles if excessive data are collected. Finally, the environment must avoid creating dependency on hints or AI explanations; reflective prompts and tasks requiring independent justification should therefore remain central.

Conclusion

This article presented a design-science framework for an intelligent learning environment tailored to teaching Systems and Signal Processing. The proposed model integrates learner diagnosis, concept-level mastery modeling, adaptive sequencing, intelligent feedback, simulation and virtual laboratory activities, project-based tasks, learning analytics, reflection, and explicit instructor control. Its central contribution is the closed-loop integration of these

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functions around discipline-specific evidence such as signal representations, system models, spectra, filter designs, code, and engineering explanations.

The framework is intended as a blueprint for implementation rather than proof of effectiveness. Scenario-based testing with synthetic learner profiles demonstrates how differentiated learning paths can be represented, but the numeric trajectories are not empirical results. The next research stage should implement a prototype and conduct an ethically reviewed evaluation with real university students, using conceptual learning, transfer, self-regulation, trust, teacher workload, and technical reliability as complementary outcome dimensions. If validated, the architecture could support a shift from static digital courseware toward adaptive, transparent, and intellectually demanding learning experiences in signals, systems, and signal-processing education.

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