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A Problem-solving Systems Approach to AI Education: Lifecycle Modules, Inter-Module Reasoning, and Values in Practice

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Work in Progress: A Problem-solving Systems Approach to AI Education: Lifecycle Modules, Inter-Module Reasoning, and Values in Practice

Abstract

Rapid advances in artificial intelligence (AI) call for engineering curricula that foster systems thinking and practical problem-solving skills in an interdisciplinary environment, areas often underserved by coding-centric computer science courses. This paper presents a systems-based approach to AI education that frames AI not as a collection of isolated algorithms, but as an interconnected lifecycle grounded in stakeholder values and real-world constraints. The approach has been implemented in a semester-long undergraduate course (AI for Smart Cities) and a week-long summer program. Course is structured around three mutually reinforcing elements: (1) AI lifecycle modules, which include Identify User Needs, Formulate AI Tasks, Select and Develop Models, Manage Data, Evaluate Performance, Analyze Errors, Refine with Feedback, Complete Solution, and Feasibility Analysis; (2) explicit inter-module relationships, such as dependencies, iteration, and error propagation across the system; and (3) critical information artifacts within each module, created using critical-thinking methods with characterization, categorization, and prioritization. Value-Sensitive Design principles (e.g., accessibility, public safety, resilience) are integrated throughout the lifecycle through stakeholder maps and trade-off matrices, ensuring that design choices are justified based on stakeholder needs. Team-based labs, peer review, and real-world projects support interdisciplinary collaboration. Preliminary self-reported pre/post survey results indicated perceived gains in students' understanding of the systems approach and related AI problem-solving competencies. The systems-based approach simplifies complex theories into accessible concepts, helping students build competencies in identifying key modules, reasoning about inter-module relationships, and critically evaluating information.

Introduction

Background and Motivation

As the urban population grows, the need for sustainable and Smart Cities (SC) has become an urgent necessity. The integration of Artificial Intelligence (AI) into the built environment, from intelligent transportation systems to infrastructure monitoring and predictive maintenance, requires a new generation of civil engineers capable of designing complex, interconnected systems [1]. This technological shift demands engineers who possess not only domain expertise but also the capability to develop, deploy, and critically evaluate AI systems within complex socio-technical contexts [2]. However, traditional AI curricula are often housed within computer science departments, focusing heavily on algorithmic syntax and coding proficiency while underserving the holistic "systems thinking" required for engineering practice [3].

This fragmented perspective, which presents machine learning as a collection of isolated algorithms, fails to prepare students for the realities of engineering practice, where AI systems must be integrated into larger infrastructure networks, satisfy diverse stakeholder requirements, navigate regulatory constraints, and account for long-term societal impacts [4]. Civil engineering students, in particular, require educational experiences that connect AI capabilities to domain-specific challenges such as transportation safety, structural health monitoring, and sustainable urban development.

Literature Review

Systems Thinking in Engineering Education. Systems thinking has emerged as a foundational competency for addressing complex engineering challenges. It is defined as "a framework for seeing interrelationships rather than things, for seeing patterns of change rather than static snapshots." [5]. Systems thinking aims to understand the whole and the many levels of interrelationship that categorize the parts of the system, enabling engineers to navigate interconnected technical and contextual dimensions [6]. The National Academies of Sciences, Engineering, and Medicine (NASEM) emphasizes shifting K-16 education toward approaches that involve more systems thinking and modeling to explain phenomena [7]. Research has identified multiple cognitive levels associated with systems thinking competency, including applying terminology and concepts, defining system boundaries, identifying and characterizing interactions within and between systems, and creating models of system behavior [8], [9]. However, assessment methods for systems thinking in engineering remain scarce compared to other science disciplines, highlighting the need for tools that can capture baseline understanding and measure learning progression [10].

AI Education and Interdisciplinary Approaches. The integration of AI concepts into engineering curricula beyond computer science has received growing attention [11]. Researchers have emphasized the need for interdisciplinary approaches that engage students from diverse fields, including civil engineering, architecture, and social sciences [12]. Studies demonstrate that incorporating authentic, real-world problems into AI education enhances student motivation and facilitates the transfer of theoretical knowledge to practical applications [13]. Recent work has begun integrating Smart City concepts into civil engineering education, recognizing that students must understand data-driven urban systems to meet workforce demands [14]. Despite these advances, significant gaps remain in understanding how to effectively teach AI within a systems framework that addresses the unique needs of civil engineering students.

Active Learning and Collaboration. To bridge the gap between theory and practice, Experimental-Centric Pedagogy (ECP) has been shown to enhance student engagement by utilizing hands-on, real-world activities [14], [15]. ECP consists of instructional methods that allow students with various learning styles to learn through hands-on practices, experiential learning, and group work. Furthermore, collaborative learning environments are linked to enhanced motivation, improved communication skills, and increased self-efficacy [16]. Research on alternative grading practices suggests that growth-oriented approaches emphasizing iterative improvement and formative feedback can enhance collaborative learning while reducing competitive pressures [17]. This component is critical to AI education because real AI work is interdisciplinary and team-based by nature: building a practical AI solution requires combining domain knowledge with data, models, and stakeholder values.

Research Gap and Purpose

Despite growing recognition of the importance of systems thinking, collaborative learning, and value-sensitive design in engineering education, few studies have examined how these elements can be integrated into a coherent pedagogical framework for AI education in civil engineering contexts. This work-in-progress paper addresses this gap by presenting a systems-based approach to AI education that integrates lifecycle modules, inter-module reasoning, and values-in-practice within a collaborative learning environment. The approach has been implemented in an “AI for Smart Cities” course in civil and environmental engineering, designed for civil, environmental, and adjacent engineering students. The research question guiding this study is: *How does a systems-based approach to AI education influence engineering students’ development of systems thinking competencies, technical foundations, and collaborative skills in civil infrastructure and Smart City contexts?*

Methodology

The methodology uses real-world smart city applications to integrate systems thinking, technical AI practice, and collaboration. The semester-long AI for Smart Cities course is an undergraduate interdisciplinary elective offered by the Civil and Environmental Engineering department, primarily for third- and fourth-year students, with an introductory Computing for Engineers course as the main prerequisite. A companion week-long summer offering at a partner institution includes students from civil, mechanical, and computer engineering. Software instruction is embedded directly in course design: students write starter-level code using an open-source Python stack, including Python, PyTorch, scikit-learn, YOLO-based computer-vision models, and notebook-based environments. The course is organized into three connected parts: lifecycle modules for systems thinking, team-based AI activities for technical and collaborative practice, and reflection for learning progression.

Part 1: Lifecycle AI Modules—A Systems Approach

To help students visualize the "big picture" before engaging with code, a systems approach incorporating lifecycle AI modules was developed. This framework includes three interconnected elements:

1. **AI Lifecycle Modules:** The lifecycle is organized into nine interconnected phases: Identify User Needs, Formulate AI Tasks, Select and Develop Models, Manage Data, Evaluate Performance, Analyze Errors, Refine with Feedback, Complete Solution, and Feasibility Analysis. To emphasize engineering constraints, the cycle explicitly integrates feasibility and user needs alongside technical tasks, ensuring students consider practical implementation from the outset.

2. **Inter-Module Relationships:** Explicit attention is given to dependencies, iteration loops, and error propagation pathways across modules. Students learn to trace how decisions in one module cascade through the system. For example, in one lab session, students worked on a traffic sign detection task to understand how environmental factors (e.g.,

lighting, occlusion, class imbalance) can propagate errors across modules. This real-world example helped students recognize that such issues often stem from non-model factors rather than algorithmic design, prompting them to consider systemic solutions.

3. **Critical Information Artifacts:** Students develop critical thinking capabilities by creating structured artifacts, such as stakeholder/value maps, requirement and risk registers, data-flow diagrams, error-analysis reports, and trade-off matrices, through characterization, categorization, and prioritization. Value-Sensitive Design principles [18] are embedded through these artifacts, requiring students to explicitly consider stakeholder values (e.g., accessibility, public safety, resilience) when making design decisions.

Rather than being taught as a stand-alone module, characterization, categorization, and prioritization are introduced through a top-down system thinking overview and then practiced in bottom-up cases such as traffic-sign and pavement-distress detection.

Part 2: Team-based Active Learning for AI Education

Collaborative learning was embedded directly into AI lifecycle activities rather than treated as a separate professional skill to improve social-cognitive outcomes [16]. Teams used the Python-based tools described above to complete lifecycle tasks, produce critical-information artifacts, critique design decisions, and revise solutions based on evidence and feedback.

- **Lab Sessions:** Labs used Experimental-Centric Pedagogy [14], [15] and real smart-city data to connect data management, model selection, evaluation, and error analysis within hands-on AI tasks.

- **Peer Review and Presentations:** Each group presented homework assignments and lab research outcomes. Students evaluated peer presentations by asking at least two critical questions related to lifecycle modules, inter-module relationships, performance limitations, stakeholder values, or solution revision. This practice helped students critique AI design decisions while improving technical communication and collaborative reasoning [17].

- **Real-world Projects:** Teams addressed open-ended problems such as pavement distress detection and pipeline condition monitoring, requiring them to move beyond algorithm tuning toward stakeholder needs, performance metrics, and value-aligned design.

Part 3: Retrospect and Reflection Design

Structured reflection and a brief pre/post questionnaire were used to help students recognize learning progression. Students submitted a one-page literature review on the first day of class before exposure to the systems approach and resubmitted a revised review after applying the framework. This comparison, together with self-reported survey items aligned with systems thinking, AI foundations, and collaboration, provided preliminary evidence of how students structured complex information and perceived the value of a systems perspective.

Preliminary Results and Discussion

The preliminary findings reported in this section aggregate student responses from both the semester-long AI for Smart Cities course and the week-long summer offering. The AI for Smart Cities implementation yielded preliminary evidence of learning gains across the three constructs named in the research question: systems-thinking competencies, technical foundations, and collaborative skills. Qualitatively, students used the lifecycle framework to connect data preparation, model training, validation, error analysis, and deployment considerations into an integrated AI pipeline. They also applied characterization, categorization, and prioritization to diagnose model-performance gaps and plan improvements. Real-world cases, including traffic-sign detection, pavement distress detection, infrastructure monitoring, and pipeline condition monitoring, helped students connect AI concepts to civil engineering problems and stakeholder values.

A small pre/post survey provided supporting evidence, though the results remain limited by sample size and the work-in-progress nature of the study. Among surveyed students, self-reported understanding of the systems approach increased from 3.06 to 4.08 on a 5-point Likert scale, ability to identify AI-system components increased from 2.75 to 3.92, confidence in applying AI to Smart City problems increased from 2.62 to 3.85, and critical-thinking confidence increased from 3.06 to 4.00. Students also reported strong perceived value in collaborative learning, peer feedback, and interdisciplinary learning. These findings do not establish causal impact, but they suggest that the lifecycle-based methodology supported the intended competencies.

Conclusion and Future Work

This work is significant to the civil engineering discipline as it proposes a scalable model for modernizing curricula to meet the demands of emerging AI technologies in urban infrastructure. By embedding Value-Sensitive Design principles, such as public safety and resilience, into the technical AI lifecycle, this approach aims to cultivate engineers who are not only technically proficient but also socially responsible. Future work will include more rigorous pre-/post-assessment using validated systems-thinking instruments [10], expansion to additional Smart City case studies, and 3- or 6-month follow-up surveys to examine longer-term engagement and AI skill use.

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