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Leveraging AI-Driven Adaptive Learning Platforms to Enhance Programming Logic in Computer Science Students

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***Abstract*—The Indian engineering education landscape currently faces a critical "Logic Gap"—a widening disparity between a student's syntactic proficiency and their ability to execute complex algorithmic problem-solving. This crisis is exacerbated by two primary stakeholder constraints: a student body often driven by rote-based credentialism over functional competence, and a faculty cohort restricted by traditional "chalk-and-talk" methodologies that fail to scale in high-enrollment environments. This paper proposes a systemic transition toward AI-Driven Adaptive Learning Platforms (ALPs) as a foundational pedagogical intervention. Unlike traditional assessment-centric tools, the proposed framework utilizes Bayesian Knowledge Tracing (BKT) and Item Response Theory (IRT) to create a dynamic, "Socratic" mentoring environment. By providing real-time, granular scaffolding and personalized learning pathways, the ALP addresses individual cognitive roadblocks that typically lead to student attrition and academic disinterest. Furthermore, the paper outlines a Hybrid-AI Implementation Strategy that empowers faculty through predictive learning analytics, shifting their role from routine troubleshooting to high-level architectural mentoring.**

***Index Terms*—AI in Education (AIEd), Adaptive Learning, Programming Pedagogy, Knowledge Tracing, EdTech Strategy.**

I. INTRODUCTION: THE CRISIS OF COMPETENCE

India produces a significant percentage of the world's engineering graduates, yet industry reports consistently highlight a staggering employability gap. In the domain of Computer Science, this gap is most visible in Programming Logic. While students may successfully navigate University examinations, they often lack the "Computational Thinking" required to solve real-world problems.

The current model is under strain from two directions: students who view the degree as a mere credential, and faculty who are often overextended or disconnected from rapidly evolving industry needs. To remain competitive in a global "AI-First" economy, the Indian classroom must evolve from a broadcast model to an interactive, data-driven environment.

II. COMPREHENSIVE STAKEHOLDER ANALYSIS: THE "LOGIC GAP" IN THE INDIAN CONTEXT

The failure of traditional programming education in India is not merely a curriculum issue; it is a systemic misalignment between two primary stakeholders. To implement an AI-driven solution, we must first deconstruct the behavioral and structural challenges inherent in the current model.

2.1. The student: Navigating the "Credentialism vs. Competence" Paradox

In the Indian scenario, the student is often a victim of a high-stakes, examination-centric culture. This results in several "pathological" learning behaviors:

- The "Scripting" Habit (Rote Memorization):

Due to a focus on passing university exams, students often memorize code snippets or "important" programs (e.g., Fibonacci series, Prime numbers) rather than understanding the underlying logic. When faced with a slight variation of the problem in a technical interview, they experience a "Logic Collapse."

- The Communication-Logic Correlation:

A significant portion of students from diverse linguistic backgrounds struggle with the English-centric nature of programming syntax and documentation. This creates a "double-barrier": they are trying to learn a complex logical framework while simultaneously overcoming a language gap, leading to a rapid decline in interest in academics.

- The Motivation-Mentoring Void:

In massive classrooms (often 60–100 students), individual identity is lost. Without a personal mentor to guide their career path or explain the "why" behind a data structure, students' default to a "minimal effort" mindset. This lack of guidance breeds indiscipline and a disconnect from the academic culture.

- Industry Blindness:

Many students are unaware of "Industry 4.0" requirements. They assume that a degree is a guaranteed ticket to a job, failing to realize that top-tier firms now prioritize algorithmic thinking and problem-solving agility over simple coding knowledge.

2.2. The faculty: The "Digital Immigrant" in a "Digital Native" World

The faculty in many Indian engineering colleges are under immense pressure, balancing high teaching loads with administrative duties. Their challenges are deeply rooted in the structural limitations of the current system:

- Overdependence on "Chalk and Talk":

Programming is a dynamic, iterative process. However, the traditional classroom setup encourages a static "broadcast" of information. Faculty often write code on a blackboard, which students copy into notebooks. This "analog" approach to a "digital" subject fails to demonstrate the live debugging and logical flow essential to coding.

- The "Upskilling" Resistance:

The IT industry evolves every 6–12 months, yet the academic cycle is often 4–5 years. Faculty members frequently find it daunting to stay updated with cloud computing, AI, or DevOps. This leads to limited upskilling and, in some cases, a resistance to change because new technologies threaten the established "lecture-notes" comfort zone.

- The Passion Gap & Inexperience:

Many junior faculty members are recent graduates themselves, often teaching because they couldn't find a role in the industry or are waiting for better opportunities. This leads to a lack of passion and a "functional" approach to teaching that fails to inspire students.

- Resource Exhaustion:

Even the most motivated faculty members cannot provide 1:1 logical feedback to 100 students simultaneously. In a 2-hour lab session, a teacher can realistically spend only 2 minutes per student—hardly enough to diagnose a deep-seated logical misconception.

III. THE AI-DRIVEN INTERVENTION: BRIDGING THE STAKEHOLDER DIVIDE

By introducing an Adaptive Learning Platform, we create a "Third Stakeholder"—an Intelligent Assistant that mitigates the weaknesses of both groups.

For the Student:

The AI provides a "Safe Space to Fail." Unlike a human instructor who may inadvertently judge a "simple" question, the AI provides infinite patience. It addresses the Lack of Interest by gamifying the logic-building process and provides the Career Guidance by showing real-world applications of every code block.

For the Faculty:

The AI serves as a "Force Multiplier." It automates the "low-level" tasks (syntax checking, basic logic errors), allowing the faculty to focus on "high-level" mentoring. This reduces the Resistance to Change because the AI handles the "latest industry standards," while the faculty focuses on the timeless principles of Computer Science.

IV. TECHNICAL FRAMEWORK: THE ARCHITECTURE OF ADAPTIVE LOGIC

The proposed AI-Driven Adaptive Learning Platform (ALP) is built on a multi-layered architecture designed to mimic the pedagogical intuition of a master-mentor.

Unlike traditional static systems, this framework treats "learning" as a dynamic data stream.

4.1. Knowledge Tracing and Student Modeling

At the core of the framework is Bayesian Knowledge Tracing (BKT) and Deep Knowledge Tracing (DKT). These algorithms allow the platform to maintain a hidden "probabilistic state" for every student across various logical competencies (e.g., control flow, data structures, recursion).

- Bayesian Knowledge Tracing (BKT):

The system models the student's knowledge as a set of binary variables (Known/Unknown). Each time a student interacts with a coding problem, the AI updates four specific parameters:

- $P(L_0) $: The probability the student already knew the logic.
- $P(T)$: The probability of learning the logic from a specific hint.
- $P(S)$: The probability of a "slip" (knowing the logic but making a typo).
- $P(G)$: The probability of a "guess" (getting it right without understanding the logic).

- Deep Knowledge Tracing (DKT):

By utilizing Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units, the platform can track how a student's performance on a "Loop" exercise in Week 2 predicts their success with "Linked Lists" in Week 10.

4.2. The Recommendation Engine: Item Response Theory (IRT)

To ensure the student is always in the Zone of Proximal Development (ZPD) the sweet spot between "too easy" and "too frustrating"—the framework employs Item Response Theory.

- Difficulty Calibration:

Every coding challenge is assigned a difficulty parameter (β).

- Discrimination Index:

The AI measures how well a specific problem distinguishes between a student who "guesses" and a student who "understands."

- Adaptive Sequencing:

If a student fails a logic gate, the IRT engine does not simply repeat the question. Its "pivots" the student to a sub-module that addresses the specific prerequisite they are missing, such as Boolean algebra, before returning to the main coding task.

4.3. NLP-Based Scaffolding and Automated Hint Generation

A critical technical hurdle in teaching programming is providing feedback that isn't just a "solution." The framework utilizes Large Language Models (LLMs) and Abstract Syntax Trees (ASTs) to provide:

- AST Analysis:

The AI parses the student's code into a tree structure. It compares this tree against a "Canonical Correct Tree." Instead of flagging a syntax error, it identifies a "Structural Deviation."

- Contextual Socratic Hinting:

Using a fine-tuned LLM, the system generates hints that ask questions rather than provide answers.

- *Example:* If a student writes an infinite loop, the AI detects the lack of an incrementor in the AST and generates: *"Your loop is currently a 'forever' journey. What variable should change inside the loop to help it reach the finish line?"*

4.4. The Learning Analytics Dashboard (The Faculty Interface)

The technical framework extends to the faculty via a Real-Time Predictive Dashboard.

- Early Warning System (EWS):

Using Random Forest Classifiers, the system flags students who show a high "Probability of Attrition" based on their interaction frequency and "Time-to-Hint" ratios.

- Concept Heatmaps:

A visual representation of class-wide logical gaps. If the "Recursion" node on the heatmap is red, the system automatically suggests a set of remedial lecture slides or interactive visualizations for the faculty to use in the next "Chalk-and-Talk" session.

V. LITERATURE REVIEW AND COMPETITIVE LANDSCAPE

The integration of technology in Computer Science (CS) education is not a new phenomenon. However, the evolution of these tools has often prioritized content delivery or competitive assessment over pedagogical scaffolding. To understand the necessity of an AI-Driven Adaptive Learning Platform (ALP), we must evaluate the current landscape and identify why existing solutions are insufficient for the foundational "Logic Gap" in Indian Tier-2 and Tier-3 institutions.

5.1. The Evolution of Programming Pedagogy

Traditional research in CS education (CSEd) has long debated the "Syntax-First" vs. "Logic-First" approach. Early literature focused on Integrated Development Environments (IDEs) as the primary tool for learning. However, modern research (2024–2026) suggests that for beginners, a standard IDE is often a "distraction-rich environment" were syntax errors mask logical misconceptions.

Recent meta-analyses of AI-assisted learning (e.g., *MDPI 2024*) show that while AI tools significantly reduce task completion time, they do not automatically improve "ease of understanding" unless they are paired with tailored pedagogical strategies. This supports our argument that AI must be an "Adaptive Mentor," not just an "Auto-complete" tool.

5.2. The MOOC Limitation: The "Visibility" Problem

Massive Open Online Courses (MOOCs) from providers like Coursera, edX, and NPTEL have democratized access to high-quality content. However, for a student in a Tier-2 Indian college struggling with basic algorithmic decomposition, MOOCs offer limited relief:

- The "Invisible" Student:

In a MOOC, unless a student posts in a forum, they are invisible to the instructor. There is no real-time intervention when a student hit a "Logic Wall."

- High Attrition:

Research indicates that MOOCs are most effective for "well-educated, self-motivated learners" (ACM Ubiquity). For the average engineering student driven by "marks" and "placement," the self-paced, un-scaffolded nature of MOOCs leads to high dropout rates.

- Passive Consumption:

Watching a video of someone else coding does not build the "mental muscle" required to write logic from scratch.

5.3. The Competitive Programming Gap: LeetCode and Hacker Rank

Platforms like LeetCode and Hacker Rank have become the industry standard for interview preparation. However, their design is fundamentally "Assessment-Centric," not "Learning-Centric."

Feature	Competitive Platforms (LeetCode/HackerRank)	Proposed Adaptive Platform (ALP)
Primary Goal	Assessment and Interview Readiness.	Foundational Logic Building.
Feedback Style	Binary (Pass/Fail) or Test Case Results.	Socratic (Hints that ask questions).
Target Audience	Intermediate to Advanced coders.	Beginners and "At-Risk" learners.
Adaptivity	Static problem sets (Easy/Med/Hard).	Dynamic paths based on Knowledge Tracing.

- The "Trial-and-Error" Trap:

On competitive platforms, students often "guess" their way to a solution by tweaking code until the test cases pass. This reinforces bad habits.

- The "Leap of Difficulty":

Moving from "Printing a Pattern" to "Dynamic Programming" is often a vertical cliff. Competitive platforms lack the Knowledge Tracing needed to build the intermediate logical bridges.

5.4. The "Vibe Coding" Trend and Industry 4.0 (2026)

As we settle into 2026, the concept of "Vibe Coding"—where AI generates and refactors code in real-time—has matured. Industry experts (IBM,

Capgemini) argue that the developer's role is shifting from "manual scripter" to "system orchestrator." In this new era, Programming Logic is more important than ever. If a student cannot decompose a problem, they cannot "prompt" an AI effectively. Our paper argues that an ALP is the only way to prepare students for this "Cloud 3.0" era, where architectural thinking and design judgment are the primary currencies of the job market.

5.5. Knowledge Tracing: The Academic Gold Standard

Our framework adopts Bayesian Knowledge Tracing (BKT), which has been proven in Intelligent Tutoring Systems (ITS) to be as effective as human 1-to-1 tutoring. Unlike HackerRank's "Stars" or "Badges," BKT provides a probabilistic model of what a student *actually knows*. This allows the ALP to skip content the student has mastered, directly addressing the "Lack of Interest" caused by redundant, "chalk-and-talk" repetition.

VI. CONCLUSION: THE PATH FORWARD FOR INDIA'S IT TALENT

The "Logic Gap" in Indian engineering education is a systemic challenge that cannot be solved by curriculum updates alone. It requires a fundamental shift in pedagogical delivery. As we move deeper into the "Agentic AI" era of 2026, the definition of a "competent engineer" has shifted from one who can write code to one who can architect logical systems.

6.1. Summary of Contributions

This paper has established that:

1. AI is a Force Multiplier: When used as a Socratic tutor rather than a solution-generator, AI restores student motivation and bridges the "Chalk-and-Talk" gap.
2. Adaptive Modeling is Essential: Systems built on Bayesian Knowledge Tracing are superior to the "Pass/Fail" models of traditional assessment platforms.
3. Faculty-AI Collaboration is the Future: The goal is not to replace the teacher but to empower them with real-time analytics, transforming the classroom into a data-driven laboratory.

To scale this success across India, institutions must:

- Adopt "Hybrid-AI" Lab Policies where 50% of practical hours are AI-mediated.
- Invest in Faculty AI-Literacy, moving teachers from "Lecturers" to "Educational Architects."
- Incorporate Logic Mastery Profiles into placement dossiers, providing recruiters with a granular view of a student's problem-solving DNA.

The transition to AI-Driven Adaptive Learning is no longer a luxury—it is a survival strategy for the Indian IT sector. By bridging the Logic Gap today, we ensure that the next generation of Indian engineers are not just coders, but the architects of the global AI economy.

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