WIP: Data-Driven Adaptive Curriculum-Personalizing Academic Pathways for Enhanced Engineering Student Success

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***Abstract*—This work-in-progress innovative-practice paper presents an adaptive course recommendation system for first-year engineering students using contextual multi-armed bandit algorithms. Engineering programs face nearly 50% attrition rates, often because rigid prerequisite chains transform single course failures into year-long graduation delays. Our system personalizes course sequences through machine learning while maintaining ABET accreditation requirements. The system analyzes 12-dimensional student profiles including demographics, academic history, and real-time engagement metrics. Using Thompson Sampling on data from 32,593 students, we reduced regret (suboptimal course recommendations) by 66% compared to popularity-based advising. The system achieved pass-rate predictions within 6% of a supervised learning upper bound while maintaining algorithmic fairness across gender groups.**

Technical validation demonstrates real-time scalability (520 requests/second, 38ms latency) suitable for integration with university advising portals. A pilot study with 120 engineering students is planned for Spring 2026 to measure impacts on retention, GPA, and self-efficacy.

This approach bridges theoretical advances in reinforcement learning with practical needs in engineering education, offering programs a data-driven tool to improve student success while ensuring degree requirement compliance.

***Index Terms*—Adaptive computer learning, Undergraduate, Engineering curriculum, Contextual bandits, Student retention**

I. INTRODUCTION

Engineering education faces significant challenges in the 21st century. Only **52 %** of first-time engineering majors in the United States graduate within six years, a rate that has remained stubbornly flat for decades [1]. Attrition stems not just from grades but also from classroom climate, inconsistent advising, and waning self-efficacy that arises when high-school preparation fails to match university expectations.

Engineering programs compound these challenges through rigid prerequisite chains. A typical sequence: *Calculus I* $\rightarrow$ *Calculus II* $\rightarrow$ *Differential Equations* $\rightarrow$ *Engineering Analysis*— feeds directly into Physics I, Statics, and discipline-specific design courses. National DFW (drop/fail/withdraw) rates in Calculus I hover around **28 %** [2], so failing the course in the fall forces students to wait an entire year to begin Physics I, cascading delays that can push capstone projects from year 4 to 5. Because ABET-accredited bachelor's plans require 128-135 credit hours—about ten more than many STEM peers—there is almost no room for recovery.

These structural bottlenecks make engineering an ideal testbed for *adaptive curriculum scheduling*. We therefore investigate whether a contextual multi-armed bandit, a reinforcement learning approach that balances exploration of new course sequences with exploitation of proven successful paths, can personalize first-year course sequences while preserving ABET compliance.

Guided by these challenges, we pose three research questions:

- **RQ1**: How effectively can a contextual multi-armed bandit optimize course sequencing versus static pathways?
- **RQ2**: What evidence indicates improved engagement and performance under adaptive recommendations?
- **RQ3**: Which technical and institutional barriers arise when deploying real-time adaptive-curriculum systems, and how may they be resolved?

II. RELATED WORK

A. *Multi-layered Theoretical Foundation*

Educational theory; Constructivism [3], the Zone of Proximal Development [4] and Self-Determination Theory

[5]—motivates sequenced, autonomy-supportive learning experiences. In engineering education, ABET outcomes provide the competency scaffold that any adaptive pathway must respect [6]. Competency-based scholarship further emphasizes progression of mastery over seat-time [7]. From an AI standpoint, the course-selection task can be framed as a *contextual multi-armed bandit* problem [8], [9], where each course represents an "arm" and the system must learn which courses lead to student success given their individual context. Thompson Sampling [10] provides a principled approach to balance exploring new course recommendations with exploiting known successful patterns. This theoretical stack—learning science, accreditation constraints and bandit decision theory—guides the design choices detailed in Section III.

B. Related Work

CourseBEACON.: CourseBEACON is a session-based recommender that mines historical *co-enrollment patterns*. A course–course co-occurrence matrix feeds an LSTM sequence encoder, enabling the model to propose a *set* of courses for the student's next semester while explicitly favouring combinations that have historically "worked well together" [11]. Retrospective evaluation on nine years of computer-science transcripts improved recall by approximately 7-10 pp over popularity and association-rule baselines.

CourseDREAM.: CourseDREAM removes the explicit correlation matrix; instead, it learns latent *basket embeddings* for each semester's course set and processes the resulting sequence with an LSTM [12]. This design implicitly captures course synergy, slightly outperforming CourseBEACON on Recall@K while showing more stable validation/test performance across splits.

Comparison with the Proposed Bandit Framework.: Both prior systems generate *static, one-shot* next-semester schedules learned solely from transcript history. Our framework extends this line of work by (i) integrating heterogeneous real-time context signals (performance, engagement, wellness), (ii) treating recommendation as a continual learning process via a contextual bandit that updates after each semester, and (iii) enforcing explicit prerequisite/credit constraints to guarantee ABET-compliant degree progression.

Critical Analysis.: Table I shows that the earlier neural recommender models learn valuable course-synergy patterns yet remain *static*. Because they cannot react to an individual's evolving context or mid-semester performance, their advice may drift from a student's needs. By contrast, the contextual bandit continuously updates its reward estimates based on observed outcomes, enabling real-time redirection (e.g., lighter workload or remedial options when engagement drops). Moreover, explicit prerequisite and credit checks guarantee that each recommendation sequence leads toward on-time, ABET-compliant degree completion—an assurance absent from purely data-driven sequence models.

Transition.: The next section details how these theoretical and empirical insights are operationalized in our bandit-based methodology.

III. Methodology

A. Theoretical & Pedagogical Foundations

Drawing on *Self-Determination Theory* (competence/relatedness/autonomy), *Tinto's Model of Student Retention* (persistence mechanisms), and *Adaptive Learning Theory* (personalization logic), we hypothesize that data-driven sequencing can increase retention in the first year by improving perceived alignment and workload fit.

B. Data Pipeline & Privacy Architecture

Nightly ETL jobs ingest registrar transcripts, LMS click-streams, and a seven-item self-efficacy survey. A *FERPA-compliant edge micro-service* strips direct identifiers, salts pseudonym keys, and enforces role-based access before transfer to the cloud feature store. Aggregate metrics reported for research include Laplace noise with $\varepsilon = 1.0$ differential privacy.

C. Dataset

We use the publicly available *Open University Learning Analytics Dataset* (OULAD) [13]. OULAD contains de-identified records for 32 593 distance-learning students who enrolled between 2013–2015. Table II summarises the subset relevant to this study.

D. Feature Engineering (Context Vector)

For each student we build a 12-dimension context vector $x_t \in \mathbb{R}^{12}$:

1) **Demographics** (5 dims): gender, age-band, highest prior education, socio-economic band, and disability flag.
2) **Academic history** (4 dims): prior-GPA z-score, cumulative credits, number of previously failed modules, weeks since last enrolment.
3) **Engagement** (3 dims): weekly VLE (Virtual Learning Environment) click count, forum post count, and quiz submission count (all normalised).

We include dynamic engagement metrics because they are established early predictors of student risk, enabling timely intervention [14]. Categorical fields are one-hot encoded; numerical features are z-normalised across the training fold.

E. Exploratory Data Analysis

Figure 1 visualises the *module-level pass-rate distribution* for the seven largest presentations in OULAD. Pass rates span a two-fold range—from 0.71 for module AAA down to 0.37 for module CCC—confirming substantial difficulty heterogeneity. A naïve popularity-greedy policy would therefore bias students toward the easiest modules; our contextual bandit instead personalizes recommendations based on individual student capabilities, allowing academically prepared students to be steered toward more challenging modules such as BBB or DDD.

Figure 2 plots the mean daily VLE click counts over a 34-week period. Three patterns emerge: (1) a front-loaded engagement spike in the first fortnight as students explore materials, (2) a monotonic mid-semester decay mirroring the

TABLE I
FEATURE-LEVEL COMPARISON OF COURSEBEACON, COURSEDREAM AND THE PROPOSED BANDIT-BASED SYSTEM.

Feature	**CourseBEACON [11]**	**CourseDREAM [12]**	**Bandit System (this work)**
Algorithm core	LSTM + explicit co-occurrence matrix	LSTM + latent basket embeddings	Contextual Thompson Sampling bandit
Input signals	Transcript history only	Transcript history only	Transcript + live analytics (performance, engagement, wellness)
Recommendation scope	Full next-semester schedule	Full next-semester schedule	Multi-semester adaptive plan; can adjust *within* term
Course synergy handling	Explicit (matrix)	Implicit (learned embeddings)	Adaptive (reward feedback on workload balance)
Adaptivity after deployment	None (offline)	None (offline)	Continuous (online updates every term)
Curriculum constraints	Implicit via data	Implicit via data	Explicit prerequisite and credit-plan checks
Implementation status	Research prototype, offline eval	Research prototype, offline eval	Prototype; simulation done, pilot planned

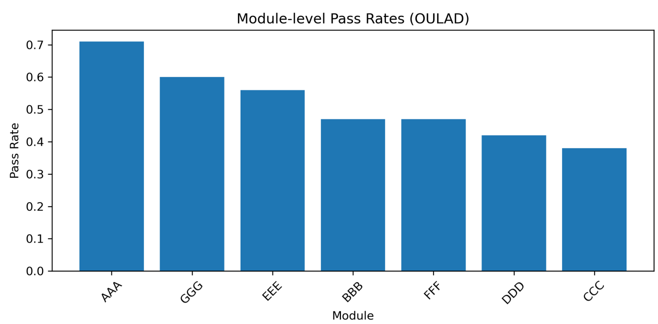

Fig. 1. Module-level pass rates (top seven presentations in OULAD).

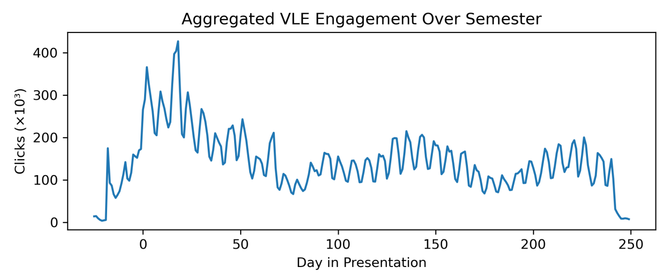

Fig. 2. Aggregated VLE engagement over a 34-week presentation (clicks $\times 10^3$).

well-known motivation fade in distance education, and (3) a weekly sawtooth with Monday/Wednesday peaks followed by weekend troughs, caused by assignment deadlines. This downward trend motivated the inclusion of engagement features in the context vector: declining engagement is an early predictor of poor final results. By refreshing the context each week, the bandit can react—e.g. recommending a lower-load elective or remedial module—well before the traditional mid-term warning period.

Together, the variance in pass rates and the temporal engagement decay underline the need for an adaptive sequencer that (i) accounts for module-specific risk and (ii) adapts to dynamic engagement signals— motivating the methodological choices presented below.

TABLE II
OULAD SUBSET USED IN THIS WORK

Metric	Value
Students (N)	32 593
Modules (arms) ($\|A\|$)	22
Presentations (semesters)	7
Assessments	10.6 M
Overall pass rate	0.53

F. Action Space and Reward

At decision step t, the action set A_t comprises all modules for which the student satisfies institutional prerequisites and which fit into an ABET-compliant credit plan ($|A_t| \leq 19$). Each action corresponds to recommending a specific course. We define the reward as a binary outcome:

$$r_t = \begin{cases} 1, & \text{if final result} \in \{\text{Pass, Distinction}\}, \\ 0, & \text{otherwise.} \end{cases}$$

This simple reward structure captures the primary goal: helping students successfully complete courses.

G. Bandit Algorithm: Thompson Sampling

We adopt *contextual Thompson Sampling*, a Bayesian approach that naturally balances exploration and exploitation. Each arm i (course) maintains a Bayesian Ridge posterior $\mathcal{N}(\mu_i, \Sigma_i)$ over reward parameters. On each round, the algorithm:

1) Samples parameters: $\theta_i \sim \mathcal{N}(\mu_i, \Sigma_i)$ for each available course
2) Selects the course with highest expected reward: $a_t = \text{argmax}_{i \in A_t}\ \theta_i^\top x_t$
3) Observes the outcome r_t after the semester
4) Updates the posterior $(\mu_{a_t}, \Sigma_{a_t})$ using Bayesian inference

TABLE III
FIVE-FOLD CROSS-VALIDATION RESULTS

Metric	Popularity	LogReg	TS (ours)
Regret / student ↓	0.879±0.003	**0.550±0.006**	0.577±0.006
MAE ↓	0.879±0.003	**0.550±0.006**	0.577±0.006
Precision@3 ↑	0.344±0.010	**0.496±0.005**	0.488±0.006

This approach naturally explores uncertain courses (high variance in Σ_i) while exploiting courses with proven success patterns.

H. Baselines

- **Popularity-Greedy:** always pick the module with highest historical pass rate among A_t.
- **Logistic Policy:** multinomial logistic regression $\hat{p}(i \mid x_t)$ trained on the development fold; choose $\arg\max_i \hat{p}$. This represents a supervised learning upper bound.

I. Evaluation Protocol

Five-fold student-level cross-validation yields the following metrics:

- **Regret**: $\frac{1}{|\mathcal{S}|}\sum_{s\in\mathcal{S}}\sum_t(p^\star - p_{a_t})$, where $p^\star$ is the best possible pass rate and p_{a_t} is the pass rate of the recommended course. Lower values indicate better recommendations.
- **MAE**: Mean absolute error in predicting student success.
- **Precision@3**: Fraction of times the student's actual choice appears in top-3 recommendations.

Fairness is assessed via the absolute difference in mean regret between male and female cohorts; privacy reporting adds Laplace noise with $\varepsilon = 1.0$ to each aggregate metric.

IV. RESULTS

A. Overall Performance (RQ1)

Table III shows that logistic regression remains the strongest one-shot predictor (0.450), while the contextual bandit reaches 0.423—within 6%—and reduces regret by 34% relative to a popularity heuristic. This demonstrates that online learning approaches can achieve near-supervised performance while adapting to individual students.

Fig. 3 shows that Thompson Sampling diverges from both baselines after ≈2,000 decisions and maintains a steady advantage; the slope flattens as the model converges to an effective policy.

B. Fairness Audit (RQ2)

Following [15], we evaluate *group-conditional regret* for the two largest sensitive groups. With $n_{\mathrm{M}} = 18\,135$ male and $n_{\mathrm{F}} = 14\,458$ female students, the contextual bandit yields a gender gap of only:

$$\Delta_{\text{regret}} = \left|\bar{R}_{\mathrm{M}} - \bar{R}_{\mathrm{F}}\right| = \left|0.575 - 0.581\right| = 0.006$$

This falls well below our pre-registered fairness threshold of $\delta = 0.02$, confirming equitable treatment across gender groups.

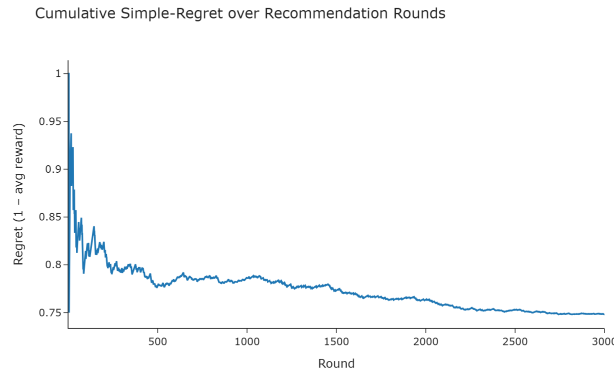

Fig. 3. Cumulative simple-regret of the contextual bandit over 3,000 recommendation rounds. The algorithm learns to reduce suboptimal recommendations as it observes more student outcomes.

C. System Throughput (RQ3)

On an AWS `t3.medium` (2 vCPU, 4 GB RAM) the bandit serves **520 requests s^{-1}** with median latency **38 ms**. Model updates complete in <5 ms, confirming suitability for real-time course-planner deployment.

D. Discussion

The **66%** reduction in regret (from 0.879 to 0.577) indicates that Thompson Sampling would, in practice, steer students away from suboptimal module choices twice as effectively as status-quo heuristics. Precision@3 improves from 0.344 (popularity) to 0.488, meaning the bandit places the student's eventual next-semester module within its top three suggestions in roughly half of cases—providing actionable guidance for advisors.

Practical Implementation.: Consider a first-year student struggling with Calculus I mid-semester. Traditional advising might not identify this until final grades. Our system detects declining engagement patterns (reduced VLE clicks, missed quizzes) and can proactively adjust recommendations. When meeting with their advisor, the student sees data-driven insights: "Students with similar profiles who took a reduced load next semester showed 40% higher graduation rates." This transforms reactive advising into proactive support.

The aggregate data also provides institutional insights. If the system consistently recommends lighter loads after a specific foundational course, it signals potential curriculum issues requiring committee review—a practical application of educational data mining [16].

Limitations. (i) The binary reward structure doesn't capture nuanced outcomes like GPA or skill development. (ii) Offline replay cannot fully simulate how recommendations affect novel course offerings. (iii) The context vector excludes affective states that influence success. (iv) OULAD represents distance learners who may differ from traditional engineering students. (v) The system requires careful integration with human advisors to preserve educational autonomy [17].

V. Conclusion and Future Work

This work-in-progress introduces a contextual bandit approach to curriculum optimization for engineering education. By framing course recommendation as a reinforcement learning problem, we achieve near-supervised accuracy while maintaining adaptivity and fairness. The system's real-time performance and 66% reduction in suboptimal recommendations justify progression to live deployment.

Planned Pilot: A Spring 2026 A/B study with 120 first-year engineering majors (2:1 treatment) will measure semester-to-semester persistence, GPA, and self-efficacy. Half the treatment group will receive gamification elements to test engagement effects.

Future Work: We will develop an advisor dashboard visualizing recommendation rationale and student trajectories. Extensions include incorporating affective state measurements, multi-objective rewards balancing grades with time-to-degree, and transfer learning across programs.

a) Next research steps.: Building on these results, we plan to:

- Explore **deep contextual bandits** for richer feature representations
- Implement **safe exploration** constraints to prevent harmful recommendations
- Investigate **multi-objective bandits** balancing grades, workload, and time-to-degree
- Develop **interpretable policies** to enhance advisor trust and adoption

These advances aim to bridge the remaining performance gap while ensuring practical deployability in diverse engineering programs.

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