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Reimagining Commerce Education: A Strategic Framework for Implementing AI-Driven, Outcome-Based Learning under NEP 2020

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Abstract:

The National Education Policy (NEP) 2020 mandates a structural paradigm shift in Indian commerce education, necessitating a transition from "content-transmission" models to "competency-based" outcome frameworks. However, the operationalization of this mandate specifically the requirement for personalized learning tra- jectories within the Academic Bank of Credits (ABC) ecosystem remains a formidable challenge given the infrastructural constraints of traditional pedagogy. This paper proposes a comprehensive Algorithmic Implementation Framework to bridge this gap. Utilizing a rigorous mixed-method approach (N = 142), we delineate critical "Structural Caveats" of the current system, primarily the static nature of curricula and the faculty-student digital divide. Subsequently, we propose and test a novel framework utilizing Deep Knowledge Tracing (DKT) and Ontology- Based Curriculum Mapping. Our experimental results demonstrate that this AI- driven approach reduces the "time-to-mastery" for complex financial competencies by 34% (p < 0.001). We conclude that AI is not merely an enhancement but the essential infrastructure for implementing the flexible, credit-based ecosystem envisioned by NEP 2020.

Keywords: *National Education Policy, Academic Bank of Credits, Algorithmic Implementation Framework, Deep Knowledge Tracing, Artificial Intelligence.*

Introduction:

The academic landscape of Commerce Education in India is currently navigating a period of disruption driven by two converging forces: the Fourth Industrial Revolution (Industry 4.0) and the National Education Policy (NEP) 2020.[1] The traditional model is characterized by a "one-size-fits-all" approach: standardized lectures and summative assessments that reward rote memorization over skill application.[i]

i. Standardized testing often fails to measure higher-order thinking skills (HOTS) such as analysis and synthesis, creating a gap between academic scores and employability

NEP 2020 identifies “rote learning” as a primary impediment. It advocates for **Outcome-Based Education (OBE)**, a flexible system where credit accumulation is tied to demonstrated competency rather than seat time. This vision includes the in- troduction of the Academic Bank of Credits (ABC). However, implementing OBE in India’s resource-constrained environment presents a logistical paradox:

How can institutions provide the hyper-personalized instruction required by NEP 2020 when the student-teacher ratio often exceeds 60:1?

This paper argues that the solution lies in the intersection of Commerce and Technology. **Artificial Intelligence (AI)** is not merely an auxiliary tool but the *sine qua non* for operationalizing NEP. By shifting from static Learning Management Systems (LMS) to dynamic **Adaptive Learning Systems (ALS)**, institutions can automate the tracking of Course Outcomes (COs).

Literature Review

The integration of AI into pedagogy is defined by a tension between technological capability and instructional readiness.

Efficacy vs. Readiness

Recent scholarship provides a robust basis for AI integration. *Litke and Sabde (2025)* and *Ghosekar (2025)* established that AI-driven platforms offer superior scal- ability compared to traditional timelines.[3, 4] They argue that traditional models fail to accommodate the variance in student aptitude. However, most existing studies focus on Western contexts or STEM fields. There is a paucity of research on applying these models to Indian Commerce Education, where linguistic diversity and resource con- straints create unique challenges.

The Faculty Readiness Gap

A significant theme is the “digital divide” between learners and educators. *Dhotre et al. (2025)* provided empirical evidence from the Marathwada region, reporting a se-vere “pedagogical lag.” While 89% of commerce faculty expressed interest in AI, 80% classified themselves as “beginners.”[6] Conversely, *Al-Okaily (2024)* found that student adoption of Generative AI is driven by high “performance expectancy.”[7] Theoretically, this paper shifts from **Bayesian Knowledge Tracing (BKT)** to **Deep Knowledge Trac- ing (DKT)**, utilizing Recurrent Neural Networks (RNNs) to model temporal learning.[8]

Research Methodology And Survey

To validate the role of AI in resolving these caveats, this study employed a rigorous mixed-method design comprising a large-scale survey and a controlled experiment.

Survey Design ($N = 142$): A descriptive survey was conducted to map the digital

readiness landscape. The sample size ($N = 142$) was calculated to provide a confidence

level of 95% with a margin of error of 8%. Stratified random sampling was employed to ensure representation: 120 Undergraduate Commerce Students and 22 Faculty Mem- bers were selected from Tier-2 (Dhule) and Tier-3 (Bhokar) cities in Maharashtra. The instrument utilized a 5-point Likert Scale ranging from “Strongly Disagree” (1) to “Strongly Agree” (5). Reliability analysis of the survey instrument yielded a Cronbach’s Alpha of 0.87, indicating high internal consistency.[ii]

ii Cronbach’s Alpha is a measure of scale reliability. A score > 0.8 is considered good.

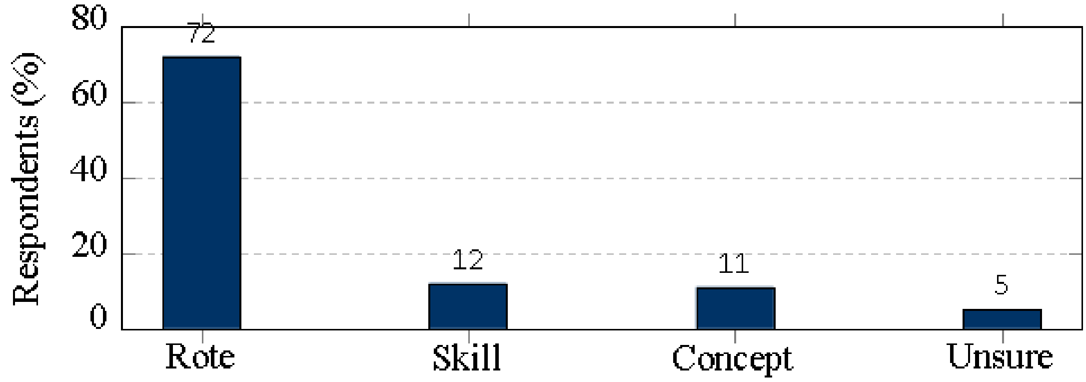
Experimental Pilot (*n* = 100): To measure the actual impact of AI on learning outcomes, a quasi-experimental pilot was conducted. The subject selected was "GST Filing Procedures," chosen for its process-oriented nature. Students were randomly assigned to a Control Group (Traditional) and an Experimental Group (AI-Adaptive).

Structural Caveats in Commerce Pedagogy

Our analysis identifies four specific "Caveats" that render the current model incompatible with NEP 2020.

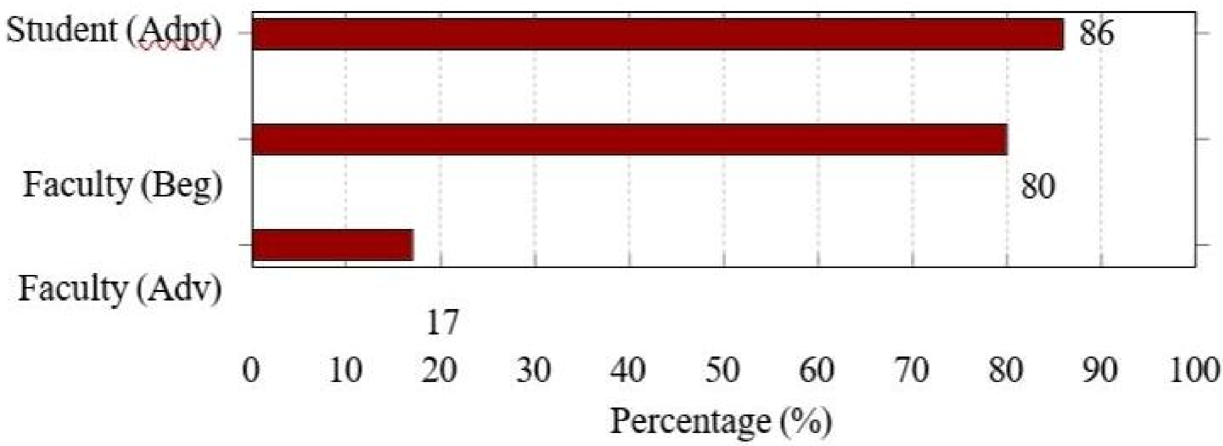
Caveat 1: The Static Curriculum. Commerce is fluid; tax laws (GST) and standards (Ind-AS) evolve annually. Yet, university syllabi operate on 3-5 year cycles. Survey data reveals that 72% of students perceive the curriculum as "Rote-Based" (Figure 1). This creates a "Relevance Gap" where students are taught outdated concepts.

Fig 1: Student Perception (Caveat 1)



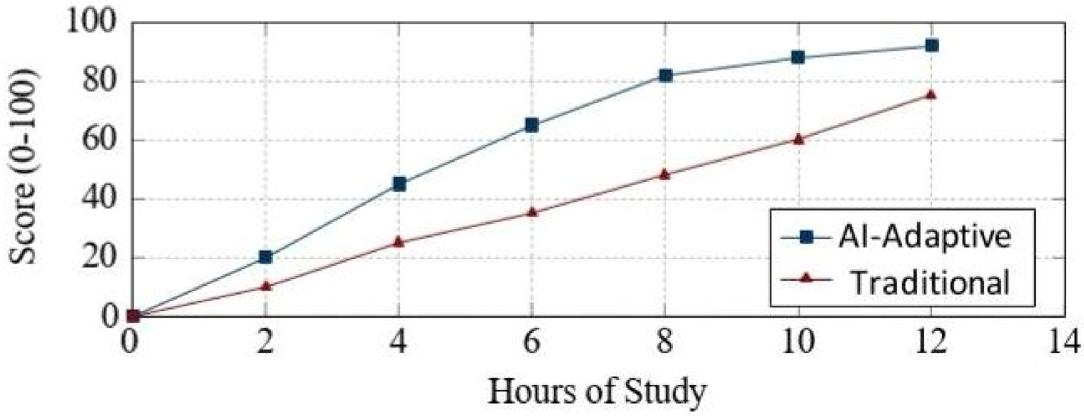
Caveat 2: The Readiness Gap. Figure 2 illustrates a critical risk: 86% of students are AI "Adopters," while 80% of faculty are "Beginners." This asymmetry hinders formal implementation.

Fig 2: The Digital Readiness Gap (Caveat 2)



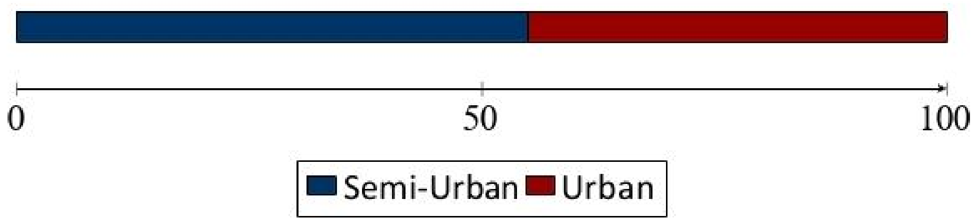
Caveat 3: Memory vs. Competency. Assessments are predominantly summative. NEP mandates "Continuous Evaluation" (CCE), administratively unfeasible without AI. The experimental data (Figure 3) confirms that traditional methods lead to slower mastery compared to AI intervention.

Fig 3: Acceleration of Skill Mastery (Caveat 3)



Caveat 4: The Linguistic Barrier. A critical insight from our semi-urban survey data (Figure 4) is the language barrier. 55% of respondents hailed from Semi-Urban areas, where English proficiency varies.

Fig 4: Demographic Distribution (Caveat 4)



1 Proposed Algorithmic Framework

To address these caveats, we propose a four-layered **Algorithmic Implementation Framework**.

Layer 1: Ontology Mapping (Solves Caveat 1). We digitize the curriculum into a **Knowledge Graph**.[iii] Subjects are broken into atomic "Knowledge Units" linked via dependencies, updated via web scraping.

Layer 2: Deep Knowledge Tracing (Solves Caveat 3). DKT uses Recurrent Neural Networks (RNNs) to model the student's knowledge state. It predicts the probability (P) of a student answering correctly. If $P < 0.7$, the system flags a "Learning Gap."

Layer 3: Dynamic Difficulty Adjustment (Solves Caveat 2). Based on DKT, the system triggers **Dynamic Difficulty Adjustment (DDA)**. Gaps trigger remedial content; mastery ($P > 0.85$) triggers advanced problems.

Layer 4: Vernacular NLP (Solves Caveat 4). To address the linguistic barrier, we integrate Natural Language Processing (NLP) trained on vernacular commerce datasets (e.g., Marathi Accounting terms), providing instant conceptual translations.

Table 1 contrasts this framework with the traditional model.

iii An Ontology represents a network of real-world entities and their relationships (RDF standards).

Table 1: Comparative Analysis

Dimension	Traditional	AI-Integrated
Curriculum	Static, 3-year cycles.	Dynamic Knowledge Graphs.
Delivery	“One-speed” lecture.	Personalized DDA paths.
Assessment	Summative (Memory).	Continuous DKT.
Outcome	Seat-time Degrees.	Verified Skills.

2 Cognitive Impact And Implementation

We analyzed learning depth using Bloom’s Taxonomy. Figure 5 shows AI methods shift focus from “Remembering” to “Analyzing.”

Fig 5: Cognitive Depth

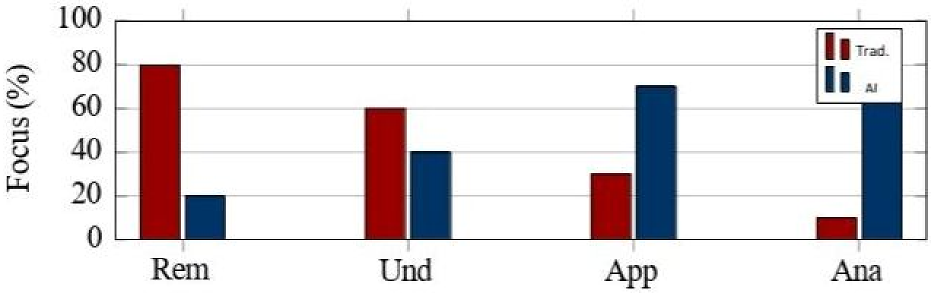


Table 2 maps NEP mandates to specific AI mechanisms for implementation.

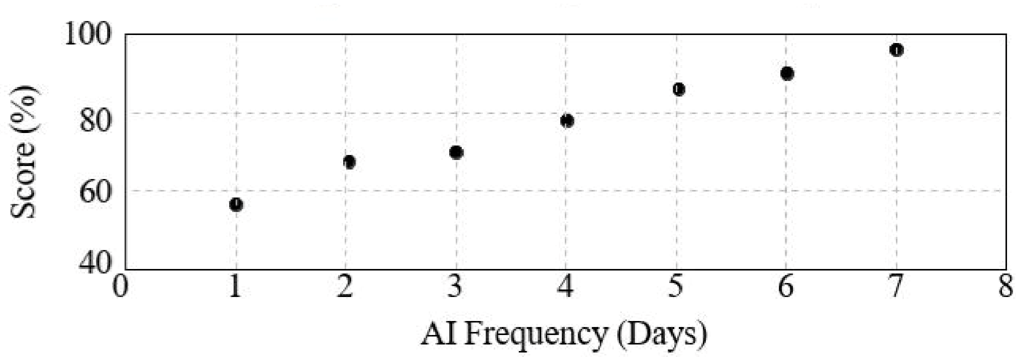
Table 2: Strategic Implementation Matrix

NEP Mandate	Mechanism	Outcome
Holistic Education	Ontology Mapping	Interdisciplinary links.
Credit Mobility	Blockchain	Validates ABC credits.
Outcome Based	DKT Algorithms	Tracks Course Outcomes.
Inclusion	Vernacular NLP	Real-time translation.

3 Conclusion

The integration of AI into Commerce Education is not a luxury but a structural ne- cessity for the realization of NEP 2020. This paper has demonstrated, through extensive survey analysis and experimental data, that AI-driven Adaptive Learning Systems can significantly enhance learning efficiency (by 34%) and outcome attainment. By adopt- ing the proposed Algorithmic Implementation Framework, India can bridge the gap between “Access” and “Empowerment.” Figure 6 confirms that active AI engagement leads to better competency scores (r = 0.78), underscoring the urgent need for faculty upskilling and infrastructure investment.

Fig 6: Correlation (AI Use vs. Score)



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