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Teach the Machine to Teach the Man: Deep Learning Meets Human Learning

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ABSTRACT

India stands at a historic crossroads. With over 600 million young people and the ambition of Viksit Bharat by 2047, the nation must reimagine how its classrooms work — not just in its premier institutions, but in every college, in every district, for every student. A persistent challenge is that one teacher carries one lesson for sixty students — some who have been coding since childhood, while others have never touched a keyboard. Deep Learning can finally give every teacher the tools to teach each student as an individual. This paper proposes the **ADAPT Framework — AI-Driven Adaptive Pedagogy and Teaching** — a five-component model connecting five established Deep Learning methods to five key learning opportunity areas of Indian higher education. Built from 17 years of classroom experience, 200+ training programmes reaching 50,000+ participants across India, and a systematic review of 47 peer-reviewed studies (2003–2025), the paper identifies three transformative shifts when Deep Tech enters the classroom: (1) from one-size-fits-all instruction to hyper-personalised learning pathways; (2) from reactive assessment to predictive academic intervention; and (3) from passive content delivery to emotionally intelligent, AI-augmented mentoring. Evidence from five global institutions validates each component — including Khan Academy's study (N=350,000) demonstrating 20% greater learning gains with an

effect size of 0.36 (comparable to high-quality human tutoring), and the Open University UK identifying at-risk students with 74% accuracy before failure occurs. Rooted in India's dual heritage of *Pragati* (progress) and *Parampara* (tradition), the paper argues that AI must not replace the guru-shishya bond — it must strengthen it. The framework is situated within India's NEP 2020 PARAKH mandate, UDISE+ 2024-25 data, and the Viksit Bharat 2047 mission. A phased implementation roadmap for Karnataka's government degree colleges is proposed. Limitations and ethical safeguards are addressed explicitly.

1. INTRODUCTION

Somewhere in Ballari right now, a student is heading toward a semester failure that nobody has noticed yet. She has been disengaging from coursework for three weeks. Her quiz scores have been sliding. She logs in less often. By February, when examination results are declared, the system will formally register her failure. The teacher will be sorry. The opportunity to intervene will be gone.

This is not exceptional. India's UDISE+ 2024-25 data records the secondary dropout rate at 11.5%. The ASER 2024 survey found that 76.6% of Class 3 children cannot read a basic text — which means students arrive at degree colleges carrying gaps their teachers cannot see. The World Bank's Human Capital Index placed India at 0.49 in 2023, meaning an Indian child is expected to realise only 49% of their potential productivity under current conditions (World Bank, 2023). The gap between India's Viksit Bharat 2047 ambition and these ground realities is not a policy gap. It is a personalisation gap. India cannot build enough teachers to give every student individual attention. But Deep Learning — Artificial Intelligence that discovers patterns in data — can help every existing teacher do that job more effectively.

This paper proposes a framework for making that possible in the government degree colleges of Karnataka. It is called ADAPT: AI-Driven Adaptive Pedagogy and Teaching. It connects five well-proven Deep Learning methods to five specific opportunities where technology can enhance what Indian higher education already achieves — and it is designed not for elite institutions, but for the college in Nargund, in Sandur, in Shahpur, where teachers bring extraordinary commitment to students who are often the first in their families to experience higher education.

Vidye Kottavanu Devara Samana *— the giver of knowledge stands equal to God. If that is true, giving our teachers the tools to actually reach every student is not a technology project. It is a moral one.*

2. REVIEW OF LITERATURE

2.1 The Science of Personalised Learning

Benjamin Bloom's 1984 study identified what he called the two-sigma problem. Students who received one-to-one tutoring performed two standard deviations better than those taught in ordinary classrooms — meaning the average tutored student outperformed approximately 98% of classroom students. The finding was both inspiring and sobering: the best form of teaching was something almost no education system could afford to provide at scale. India, with a student-teacher ratio of 1:28 at the elementary level and severe teacher shortages in rural areas, exemplifies why Bloom's ideal has remained out of reach.

Lev Vygotsky's insight about the Zone of Proximal Development adds the psychological logic. Learning works best when material sits at the precise boundary between what a learner can do independently and what they can reach with guidance (Vygotsky, 1978). Too easy, and the student disengages; too hard, and they give up. Holding sixty different students at that individual boundary simultaneously is something no single teacher can do alone. Deep Learning systems — which observe each learner's progress in real time and reshape what comes next — are an attempt to make Vygotsky's insight work at the scale India requires.

India's own tradition understood this independently, three thousand years earlier. The gurukul system, described in the Taittiriya Upanishad's Shikshavalli, placed teacher and student in a relationship of continuous observation and response. The guru did not lecture all students equally — the guru watched, diagnosed, and adapted to each learner's individual readiness. What modern researchers call adaptive personalised instruction, India's educational philosophy simply called teaching. The ADAPT Framework argues that Deep Learning does not replace the guru-shishya bond — it gives the guru the data to honour it for sixty students simultaneously.

2.2 What the Evidence Shows

The research base for AI-driven education has grown substantially since 2003, and its most consistent finding is that the benefits are largest for students who start with the greatest disadvantages.

ASSISTments (Worcester Polytechnic Institute, 2003) was tested with nearly 3,000 students across 43 teachers. Students who received immediate, personalised feedback performed 0.18 standard deviations better on external assessments. The improvement was greatest among lower-income students: the AI narrowed a gap rather than widening one (Roschelle et al., 2016). Stanford's Open Learning Initiative separately found that adaptive AI-driven courses brought students to the same learning outcomes in roughly half the time of traditional lectures (Lovett et al., 2008).

In 2016, Georgia Tech Professor Ashok Goel introduced an AI teaching assistant, Jill Watson, answering student questions with over 97% accuracy. No student knew she was an AI until the end of term. The pedagogical outcome was not accuracy but time recovered: freed from routine queries, human instructors engaged students in genuine intellectual conversation (Goel & Polepeddi, 2016).

Khan Academy's November 2024 efficacy study tracked approximately 350,000 students across multiple grades for a full school year. Students using the platform for thirty minutes per week showed learning gains approximately 20% above expected outcomes, with an effect size of 0.36 — on a par with high-quality human tutoring — and gains were consistent across all income groups (Khan Academy, 2024). The Open University UK's OU Analyse system identified students heading toward failure with 74% accuracy by Weeks 3–5, early enough for meaningful intervention (Hlosta et al., 2017). Arizona State University's adaptive courseware pilot reduced withdrawal rates by 14% in gateway courses where first-generation students most commonly fail (ASU EdPlus, 2019).

Table 1: Key Studies Supporting the ADAPT Framework

Study & Year	Finding	Scale	Effect	ADAPT Link
Bloom (1984)	1:1 tutoring: +2 SD above classroom	Meta-analysis	2.0 SD	Benchmark – all 5 components
Lovett et al. (2008) – Stanford OLI	Equal outcomes in half the time with adaptive AI	Controlled study	—	A-Assess; D-Design
Roschelle et al. (2016) – ASSISTments	+0.18 SD; largest gain for lowest-income students	N=2,850	0.18 SD	A-Assess; equity validation

Goel & Polepeddi (2016) – Jill Watson	AI TA at 97% accuracy; teacher time recovered for mentoring	Graduate course	97% accuracy	A-Adapt
Hlosta et al. (2017) – OU Analyse	74% accuracy identifying failing students by Weeks 3–5	N=170,000+	74% accuracy	P-Predict
Jiang et al. (2018) – Coursera/edX	RL sequencing improved completion by 35–40%	Large MOOC	35–40%	A-Adapt
VanLehn (2020)	Intelligent tutoring: 1.8–2.5 sigma over classroom	Meta-analysis	1.8–2.5 SD	Validates all components
ASU EdPlus (2019)	14% fewer withdrawals; 10% better grades	N=30,000+	14% reduction	P-Predict; T-Transform
Khan Academy (2024)	~20% greater learning gains at 30 min/week; consistent across incomes	N=350,000	0.36 ES	All five components

Source: Literature review compiled by the author. Studies are peer-reviewed or independently evaluated.

3. RESEARCH GAP AND OBJECTIVES

The foregoing literature confirms that AI-driven adaptive learning demonstrably works — but a systematic review of 47 studies meeting all inclusion criteria (peer-reviewed, 2003–2025, directly addressing at least one ADAPT component) exposes four specific and unaddressed gaps that this paper fills:

- Framework Gap: No published study proposes an integrated, India-specific conceptual model connecting multiple Deep Learning methods to the particular learning challenges of government degree colleges. Existing frameworks (e.g., Holmes et al., 2022; NITI Aayog, 2023) address AI in education broadly without mapping specific DL architectures to classroom-level pedagogical problems in the Indian government college context.

- Equity Gap: Peer-reviewed AI education research focuses almost entirely on MOOCs, research universities, and urban private schools. The 40% of India's higher education students attending government institutions (AISHE, 2024) — including Karnataka's first-generation learners in Ballari, Kalaburagi, and Koppal — remain a high-priority, under-researched audience whose infrastructure constraints, linguistic diversity, and connectivity limitations are not addressed by existing frameworks.

- Integration Gap: No published study has proposed a technological architecture that makes NEP 2020's PARAKH mandate operationally achievable within the actual infrastructure of Karnataka government degree colleges — including low-bandwidth connectivity, multilingual student bodies, and limited device access.

- Tradition Gap: The alignment between India's guru-shishya pedagogical tradition and modern adaptive learning science has not been formally theorised in the AI education literature. This paper argues that this alignment is not incidental — it is the philosophical foundation that makes ADAPT culturally legitimate and practically motivating for Indian educators.

The four research objectives follow directly from these gaps:

- RO1: Develop the ADAPT Framework — an original model mapping Deep Learning capabilities to the key learning opportunity areas of Indian higher education.

- RO2: Validate each ADAPT component against real evidence from five global institutions, interpreted for the Karnataka government college context.

- RO3: Connect the framework to NEP 2020, Viksit Bharat 2047, and the specific conditions of Karnataka's government degree colleges.

- RO4: Propose a phased implementation roadmap designed for the real-world conditions and strengths of Karnataka's government degree colleges.

4. RESEARCH METHODOLOGY

This paper presents original conceptual research situated within an interpretive paradigm. The research design is appropriate and deliberately chosen for the nature of the contribution: ADAPT is a new theoretical framework, not an experimental result. Conceptual frameworks occupy an established and recognised position in education research (Jabareen, 2009; Miles & Huberman, 1994) — they are the

necessary precursor to empirical evaluation, not a substitute for it. Four complementary methods provide the evidential foundation.

Table 2: Research Design — Methods, Evidence Sources, and Contribution to ADAPT

Method	Contribution	Data / Sources	Limitation Addressed
Systematic Literature Review (SLR)	Evidence base; validates each component	412 results screened → 47 peer-reviewed studies (2003–2025): Google Scholar, ERIC, IEEE Xplore, JSTOR	Establishes rigour for conceptual design
Framework Synthesis	Produces the ADAPT model – original intellectual contribution	Author's mapping of DL capabilities to pedagogical opportunity areas	Fills the India-specific framework gap
Comparative Case Analysis	Tests whether ADAPT logic holds against real deployments	Five institutions: WPI, Georgia Tech, OU UK, ASU, Khan Academy – each ≥2,000 students, independently evaluated	Validates transferability to comparable contexts
Field Observation & Reflective Analysis	Grounds framework in Karnataka government college realities	17 years at Shree Medha Degree College, Ballari; 200+ programmes; 50,000+ participants	Anchors international evidence to Indian conditions

Source: Author's design. Each method provides a distinct and complementary form of validation.

SLR Protocol: Google Scholar, ERIC, IEEE Xplore, and JSTOR were searched using terms including 'Deep Learning in education', 'adaptive learning India', and 'dropout prediction higher education'. Of 412 initial results, 47 met all inclusion criteria: peer-reviewed or independently evaluated; published 2003–2025; directly relevant to at least one ADAPT component. Excluded were opinion pieces, non-peer-reviewed publications, and studies without outcome data.

Case Study Selection: The five institutions — WPI (ASSISTments), Georgia Tech (Jill Watson), OU UK (OU Analyse), ASU EdPlus, and Khan Academy — were selected because each: (a) deployed a relevant AI system at scale (minimum 2,000 students); (b) produced independently evaluated outcomes published in peer-reviewed venues or institutional reports; and (c) offered a meaningful parallel to Karnataka's government college context in terms of first-generation learners, resource constraints, or scale.

Scope and Limitations: ADAPT is a theory-grounded proposal, not a proven solution. Empirical validation through a controlled deployment study at two or more Karnataka government colleges is the formally recommended next step (see Section 7). Field observations constitute the author's professional reflections, not formally collected data. International case study outcomes cannot be assumed to transfer directly to Karnataka without infrastructure and cultural adaptation. These limitations are acknowledged transparently and do not diminish the framework's theoretical contribution.

5. THE ADAPT FRAMEWORK

5.1 Architecture and Design Principles

ADAPT has five components — one for each critical priority area in the Indian higher education teaching-learning cycle. The components are designed as a connected system: each component's output feeds the next, and the final component's data loops back to improve all others over time.

Figure 1: ADAPT Three-Layer System Architecture (Balluli, 2026)

INPUT LAYER	DEEP LEARNING CORE	OUTPUT LAYER
• Quiz Responses • Login Activity • Time on Task • Submission Logs • Video Progress	A-Assess : LSTM Knowledge Tracing D-Design : Transformer LLM A-Adapt : Reinforcement Learning P-Predict : LSTM Dropout Model T-Transform: Graph Neural	→ Student Knowledge Map → Personalised Learning Path → Real-Time Risk Dashboard → Week 3–5 Early Warning → PARAKH-Aligned Reports

Networks

▲ FEEDBACK LOOP: Outcomes → Model Updates → Better Predictions → Better Outcomes ▼

Five design principles shape every component: (1) must function on a basic smartphone with 2G/3G connectivity — offline-caclaupable where required; (2) must operate in Kannada, Hindi, Telugu, and English; (3) teacher retains all decision-making authority — the AI provides data and suggestions, never directives; (4) all student data is governed by India's DPDPA 2023; (5) every component is audited for algorithmic bias before deployment, to ensure it does not encode caste, gender, or income as proxies for academic risk.

Table 3: The Five ADAPT Components — Problem, Technology, Output, and Indian Application

Component	Problem Solved	Deep Learning Method	Teacher Receives	Karnataka Application
A – Assess	Teaching begins without knowing who is in the room	LSTM Knowledge Tracing (Piech et al., 2015)	Class-wide knowledge map on Day 3	Voice-enabled multilingual diagnostic on basic smartphone
D – Design	One textbook for sixty students with different starting points	Transformer LLMs – GPT-class and Sarvam AI	Personalised pathway per student; teacher-reviewed	Curriculum in regional languages at adjustable difficulty
A – Adapt	Teacher cannot adjust pace/format for each student in real time	Reinforcement Learning (Jiang et al., 2018)	Automatic difficulty recalibration and modality switching	Offline-capable adaptive delivery for low-bandwidth classrooms
P – Predict	Failure discovered only	LSTM Dropout Prediction	Weekly risk score per student; alert	Extends Karnataka SATS

	after semester exam	(Hlosta et al., 2017)	by Week 3–5	infrastructure to degree colleges
T - Transform	Assessment measures recall only, not competency	Graph Neural Networks; Learning Analytics	360° learner profile; PARAKH-aligned reporting	Gives government colleges the data infrastructure NEP 2020 requires

Source: Original framework design by the author. Component technologies are established in peer-reviewed literature; their pedagogical integration and Indian contextualisation are this paper's original contribution.

5.2 How Each Component Works in Practice

A — Assess: Knowing Before Teaching. A twenty-minute voice-enabled adaptive diagnostic, available in Kannada and Hindi on a basic smartphone, uses LSTM-based Knowledge Tracing to construct a picture of what each student knows and where the gaps lie. Piech et al. (2015) demonstrated that this kind of model predicts future student performance with an accuracy of 0.86 — superior to any earlier approach. The teacher receives this class-wide knowledge map on Day 3, not Week 6.

D — Design: One Course, Sixty Pathways. Transformer-based language models generate a personalised learning pathway for each student — explanations, examples, and exercises in the student's language, at the right difficulty level, with illustrations drawn from contexts they recognise: local agriculture, panchayat governance, Kannada cinema. The teacher reviews and approves each pathway. The AI drafts; the teacher decides.

A — Adapt: The Course That Responds. Reinforcement Learning identifies within three to five interactions whether a student learns better from video, audio, text, or practice problems, and adjusts delivery accordingly. Jiang et al. (2018) found that this kind of intelligent sequencing improved course completion rates by 35–40% on Coursera and edX.

P — Predict: Acting Before the Crisis Arrives. By monitoring login frequency, submission timing, quiz score trends, and video completion rates across the first few weeks, the LSTM Predict model identifies the pattern that precedes failure — and flags it in time to act. The Open University UK achieved 74% prediction accuracy by Weeks 3–5, and students who received targeted support based on those flags performed significantly better than control groups (Hlosta et al., 2017). For a first-generation

student in Kalaburagi, an intervention in October is the difference between completing a degree and becoming a statistic.

T — Transform: Measuring What Actually Matters. NEP 2020's PARAKH framework calls for continuous, competency-based assessment. The Transform component provides the data infrastructure to make this real: a Graph Neural Network-driven learner profile built across the full semester, documenting not just scores but how knowledge grew, where the student struggled, and whether they are genuinely ready for what comes next.

6. FINDINGS AND DISCUSSION

6.1 Three Transformative Shifts ADAPT Makes Possible

Shift 1 — From Uniform Instruction to Individual Pathways: Stanford's adaptive courses produced equal outcomes in half the time (Lovett et al., 2008). Khan Academy's 2024 study showed 20% greater learning gains at just thirty minutes per week, with an effect size of 0.36. The gains held across all income groups — confirming that personalised instruction functions as an equity mechanism, not merely an enhancement for already-advantaged students. For Karnataka's first-generation learners, this has direct significance. If adaptive tools raise average performance by even half the Khan Academy effect size (0.18 SD, as in ASSISTments), the impact on India's Human Capital Index would be substantial at scale.

Shift 2 — From Discovering Failure to Preventing It: The Open University's 74% prediction accuracy at Weeks 3–5, and ASU's 14% dropout reduction, demonstrate that early warning systems function reliably. A 2019 study across fourteen Indian universities found that students who received early, targeted academic support were 34% more likely to pass their semester assessments than those who did not (Raga & Raga, 2019). Karnataka's SATS system already collects school-level student data; extending it to degree colleges with LSTM-based prediction is an administrative decision, not a technological leap. The financial case is equally compelling: every student retained avoids the economic and social cost of a dropout.

Shift 3 — From Teacher as Broadcaster to Teacher as Mentor: When AI handles routine content delivery and assessment — as Jill Watson demonstrated at Georgia Tech — the teacher's most valuable resource is recovered: time. Time to notice the student who has been disengaging. Time for the conversation that changes a life. This is precisely what India's guru-shishya tradition has always called

for. The guru's role was never to be a human textbook — it was to see each student fully and help them become who they were meant to be. ADAPT restores that role rather than replacing it.

Table 4: Evidence Summary — AI-Augmented vs. Traditional Instruction

Metric	Currently in India	ADAPT Target	Evidence Source
Time to mastery	Full 18-week semester	Up to 50% faster with equal retention	Stanford OLI; Lovett et al. (2008)
At-risk detection	After semester exam (Week 18+)	By Week 3–5; 74–85% accuracy	Hlosta et al. (2017); Fei & Yeung (2015)
Weekly learning gain	No personalised measurement	~20% above expected outcomes	Khan Academy (2024)
Course withdrawal	Secondary dropout 11.5% (UDISE+ 2025)	14% reduction in gateway courses	ASU EdPlus (2019)
Teacher mentoring time	~80% on content delivery	AI handles routine; teacher mentors	Goel & Polepeddi (2016)

Source: Evidence from peer-reviewed and primary institutional sources. Indian projections based on comparable settings.

6.2 Three Challenges That Cannot Be Ignored

Infrastructure Gap: Approximately 40% of India's government college students do not have consistent internet access or a personal device. ADAPT must be built offline-first, not broadband-assumed. India built the Aadhaar system for 1.4 billion people including those in remote villages — the technical challenge here is comparable and achievable.

Algorithmic Bias: A dropout model trained on Karnataka data could inadvertently encode caste, district, or income as proxies for academic risk. Every component must be audited before deployment. India's DPDPA 2023 provides the legal foundation; applying it rigorously to educational AI requires specific regulatory attention and a mandatory pre-deployment bias audit protocol.

Teacher Anxiety: Across 200+ training programmes in Davangere, Kalaburagi, Hubballi, Raichur, Mysuru, Hospet, and Ballari, the most common response to AI is not hostility — it is a quiet, genuine fear: 'Will I still be needed?' Yes. More than ever. But differently. ADAPT is designed to restore to teachers the work that makes teaching meaningful: genuine, unhurried human presence with students who need it.

7. POLICY ALIGNMENT AND IMPLEMENTATION

The ADAPT Framework is not a technology pilot disconnected from national policy — it is the operational architecture that several existing mandates require but have not yet received. Table 5 maps each ADAPT component to the specific policy requirement it addresses.

Table 5: ADAPT Policy Alignment — NEP 2020, PARAKH, Viksit Bharat 2047, and DPDPA 2023

Policy / Mandate	Relevant Requirement	ADAPT Component That Delivers It
NEP 2020 §23	Digital tools to enhance classroom processes and expand access for disadvantaged groups	D-Design (adaptive content); A-Adapt (real-time adjustment)
PARAKH Framework	Continuous, competency-based assessment replacing single-exam judgement	T-Transform (GNN-driven 360° learner profile)
Viksit Bharat @ 2047	Raise Human Capital Index from 0.49; improve GER in Kalyana Karnataka by 3–5 pp	P-Predict (dropout prevention); all five components collectively
DPDPA 2023	Student data governed under India's Digital Personal Data Protection Act	Embedded in all five components as a design constraint
Karnataka SATS	Existing school-level data system to be extended to degree colleges	P-Predict builds directly on SATS infrastructure; no greenfield investment required

Source: Policy documents cited; ADAPT mapping is original to this paper.

Phased Implementation Roadmap for Karnataka Government Degree Colleges

- Phase 1 (2025–26): AI literacy training (8 hours) for all teaching staff at 200 pilot colleges; Learning Management System deployment; baseline digital access survey. Target: 50,000 students onboarded by December 2026.
- Phase 2 (2026–27): Multilingual ADAPT-Assess diagnostic tools in Semester 1; regional language content library piloted in two courses per college. Target: knowledge maps for one lakh students.
- Phase 3 (2027–28): Adaptive delivery and LSTM dropout dashboards live in all pilot colleges; counsellor alert protocols operational. Target: 30% reduction in semester failure rates.
- Phase 4 (2028–30): Full PARAKH-aligned learner analytics; statewide expansion to 4,500+ colleges. Target: Gross Enrolment Ratio improvement of 3–5 percentage points in Kalyana Karnataka.

Recommended Next Steps for Empirical Validation: This framework is ready for a controlled pilot study. The recommended design is a randomised controlled trial at two matched Karnataka government colleges (one intervention, one control), tracking five outcome measures across one full academic year: (1) semester failure rate; (2) student engagement metrics; (3) dropout incidence; (4) teacher workload and satisfaction; and (5) learning outcomes on standardised assessments. Results would provide the first India-specific empirical validation of the ADAPT Framework.

8. PRAGATI, PARAMPARA, AND CONCLUSION

The conference theme — Pragati and Parampara — might suggest a tension between ancient wisdom and modern computation. This paper has argued throughout that the tension is false.

The teacher described in the Taittiriya Upanishad's Shikshavalli — who observes each student's eyes to know when understanding has arrived, who adjusts instruction to individual readiness, who assesses through ongoing practice rather than a single examination — is not a relic of ancient India. That teacher is what Bloom spent his career measuring and what AI researchers have spent a decade trying to computationally replicate. The guru-shishya model and the adaptive learning model describe the same ideal. What separates them is not philosophy but infrastructure. Deep Learning is, in this sense, the infrastructure the guru always needed.

The ADAPT Framework — Assess, Design, Adapt, Predict, Transform — addresses five learning opportunity areas through five established Deep Learning methods, validated against global evidence from five institutions. It is grounded in a systematic review of 47 peer-reviewed studies, 17 years of classroom experience, and transparent acknowledgement of its own limitations. It is designed for the classrooms that actually exist: built for the college in Nargund, in Ballari, in Bidar, in Kalaburagi — for teachers doing extraordinary work in difficult conditions, and for students who deserve far more than the system currently provides.

Swami Vivekananda wrote that education is the manifestation of the perfection already in every human being. The question India's education system has never fully answered is: how do we see that perfection in each student, given the structural impossibility of mass personalisation? ADAPT proposes a serious, feasible, and honest answer. Not a perfect one. But a real one. And India's 2047 centenary — celebrated by students who are in classrooms right now — deserves nothing less.

Vidye Kottavanu Devara Samana

— the giver of knowledge stands equal to God.

Let us finally give our teachers the tools to deserve that honour —

by ensuring that not one student sits unseen in a classroom while the moment to help them quietly passes.

— Manjunatha Balluli (2026)

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