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# Evolution of Artificial Intelligence and Machine Learning: A Paradigm Shift in Smart Education

**Dr. Muttappa M. Mantur**[1]

[1]Associate Professor and Head, Department of Computer Science, Government First Grade College for Women, Jamkhandi, Karnataka, India. (Affiliated to Karnataka State Akkamahadevi Women's University, Vijayapura). manturmutturaj77@gmail.com

**Abstract:**

Artificial Intelligence (AI) and Machine Learning (ML) have moved from laboratory curiosities to everyday infrastructure of teaching and learning. This article traces the evolution of AI and ML across seven decades and argues that their convergence with education represents a genuine paradigm shift: from standardised, teacher-centered transmission to adaptive, data-informed and learner-centered ecosystems that are called "smart education". Using a structured narrative review of landmark and contemporary literature, the paper (i) proposes a four-era periodisation of AI in education (rule-based, statistical, deep-learning and generative-foundation-model era); (ii) introduces the Five-Layer Smart Education Framework (FLSEF), which links data, intelligence, pedagogy, governance and human agency; (iii) presents an AI Maturity Model for Educational Institutions with five levels; and (iv) discusses ethical, equity and institutional challenges with specific reference to the Indian higher-education context under the National Education Policy 2020. The paper concludes that the central question has shifted from whether AI can teach to how institutions can govern it so that it augments, rather than replaces, human educators. Directions for empirical research are proposed.

**Keyword:**

- Artificial Intelligence;
- Machine Learning;
- Smart Education;
- Intelligent Tutoring Systems;
- Learning Analytics;
- Generative AI;
- Personalised Learning;
- Higher Education;
- NEP 2020

## INTRODUCTION:

Education systems have always been shaped by the dominant information technology of their time: the blackboard, the printed textbook, broadcast media, the personal computer and the internet. AI and ML are the latest, and arguably the most consequential, of these technologies, because they do not merely deliver content; they model learners, generate content, make predictions and increasingly take part in pedagogical decisions (Holmes, Bialik and Fadel, 2019; Luckin et al., 2016).

The term smart education is used in this paper to describe learning environments in which sensing, data analytics, ML models and AI-driven interfaces are integrated so that instruction, assessment, support and administration respond dynamically to individual learners and institutional needs. It extends earlier notions of e-learning and blended learning by adding the capacity to learn from data and act on it.

Three developments make the present moment distinctive. First, the volume of educational data produced by learning management systems, MOOCs, mobile apps and campus systems has grown

enormously. Second, deep learning and the transformer architecture (Vaswani et al., 2017) have produced foundation models capable of language, image and code understanding at a scale unimaginable a decade ago (Bommasani et al., 2021). Third, public-facing generative tools have reached students and teachers directly, without institutional mediation, forcing a rapid rethink of curriculum, assessment and academic integrity (Kasneci et al., 2023).

Existing reviews have documented applications of AI in higher education and noted that much research is led by computer scientists with limited educator involvement (Zawacki-Richter et al., 2019). What is still needed is an integrative account that connects the technical evolution of AI/ML with the pedagogical and institutional change it demands. This paper addresses that gap.

**RESEARCH QUESTIONS:**

- RQ1: How have AI and ML paradigms evolved, and how has each stage shaped educational technology?
- RQ2: What makes the current convergence a paradigm shift rather than incremental tool adoption?
- RQ3: What framework can guide institutions, especially public colleges and universities in developing contexts, in adopting AI responsibly?

**Contributions:** The paper offers (1) a four-era periodisation linking AI/ML advances to educational applications, (2) the FLSEF conceptual framework, (3) a five-level institutional maturity model, and (4) a research agenda.

## 2. METHODOLOGY

The study is a conceptual, structured narrative review. Sources comprised foundational works in AI and ML, seminal papers on intelligent tutoring, educational data mining and learning analytics, recent reviews of AI in education, and policy documents (UNESCO, Government of India). Selection was purposive: works were included if they (a) introduced or consolidated a major technical paradigm, (b) reported evidence on educational effectiveness, or (c) shaped policy or ethical debate. The synthesis was thematic and proceeded in three steps: chronological mapping of technical paradigms, mapping of corresponding educational applications, and abstraction of cross-cutting design and governance principles into a framework.

Because the review is narrative rather than a PRISMA-style systematic review, it does not claim exhaustive coverage. Its value lies in synthesis and theory building, and the framework proposed should be treated as a hypothesis for empirical testing (Section 8).

## 3. EVOLUTION OF AI AND ML: A CONCISE TECHNICAL HISTORY

### 3.1 FOUNDATIONS (1940S TO 1960S)

Turing (1950) posed the question of machine intelligence and proposed an imitation-based test. The 1956 Dartmouth proposal by McCarthy and colleagues gave the field its name. Early AI emphasized symbolic reasoning and search. In parallel, Samuel (1959) demonstrated that a program could improve its play of checkers from experience, an early and influential statement of what became machine learning.

### 3.2 KNOWLEDGE-BASED AND EXPERT SYSTEMS (1970S TO 1980S)

The field turned toward encoding human expertise as explicit rules. In education this produced the first intelligent computer-assisted instruction; Carbonell (1970) argued for systems that could represent subject knowledge and engage in dialogue rather than merely drill. The era's strengths were transparency and traceability; its weaknesses were brittleness and the high cost of knowledge engineering.

### 3.3 STATISTICAL AND CLASSICAL ML (1990S TO 2000S)

With more data and computing power, the field shifted to learning from examples. Decision trees, support vector machines, Bayesian networks, ensemble methods and clustering became mainstream (Mitchell, 1997). Educational applications included Bayesian knowledge tracing (Corbett and Anderson, 1995), early-warning prediction of student dropout, and the emergence of educational data mining (Baker and Inventado, 2014).

### 3.4 DEEP LEARNING (2010S)

Back propagation (Rumelhart, Hinton and Williams, 1986) matured into deep architectures that achieved breakthroughs in vision, speech and language (Krizhevsky, Sutskever and Hinton, 2012; LeCun, Bengio and Hinton, 2015). Reinforcement learning (Sutton and Barto, 2018) added sequential decision-making. In education, deep knowledge tracing (Piech et al., 2015), automated essay and short-answer scoring, speech-based language tutors, and computer vision for engagement estimation appeared.

### 3.5 FOUNDATION MODELS AND GENERATIVE AI (2020S)

Transformers (Vaswani et al., 2017) and large-scale pre-training produced models that perform many tasks from instructions or a few examples (Brown et al., 2020). For education this is qualitatively new: a single system can explain, translate, summarize, generate practice questions, give feedback and hold a tutoring-style dialogue in many languages. At the same time, such systems can produce fluent but incorrect content, reflect training-data bias and challenge conventional assessment (Kasneci et al., 2023).

## 4. FOUR ERAS OF AI IN EDUCATION

**Table 1 synthesizes the technical history with educational practice, forming the periodisation proposed here.**

| Era | Dominant paradigm | Typical educational applications | Role of the learner | Role of the teacher | Principal limitation |
|---|---|---|---|---|---|
| 1.Rule-based (1960s to 1980s) | Symbolic AI, expert systems | Early ICAI, drill-and-practice, rule-based tutors | Recipient of structured feedback | Content designer, system supervisor | Brittleness, high authoring cost |
| 2. Statistical (1990s to 2000s) | Classical ML, Bayesian models | Knowledge tracing, dropout prediction, recommender systems, EDM | Source of behavioural data | Interpreter of dashboards | Narrow, feature-engineered models |
| 3. Deep learning (2010s) | Neural networks, RL | Deep knowledge tracing, automated scoring, speech and vision analytics, adaptive platforms | Co-producer of rich multimodal data | Orchestrator of adaptive tools | Opacity, data hunger, bias |
| 4. Generative-foundation (2020s onward) | Large pre-trained models | Conversational tutors, content generation, feedback, translation, coding assistants | Active prompter and co-creator | Learning designer, curator, ethical guide | Hallucination, integrity, dependence, governance gaps |

**Table 1. Four-era periodisation of AI in education (author's synthesis).**

Two observations follow. First, each era did not replace the earlier one; rule-based logic, statistical models and neural systems now coexist inside modern platforms. Second, with each era the locus of intelligence moved from hand-coded expertise, to engineered features, to learned representations, and finally to general-purpose models that the educational institution does not itself train. This last shift, from building to procuring and governing AI, is the heart of the present institutional challenge.

## 5. WHY THIS IS A PARADIGM SHIFT

The word paradigm is used deliberately. Following Kuhn's sense of a change in the shared assumptions of a field, we argue that AI and ML alter five assumptions on which formal education has long rested.

1. **From the average learner to the individual learner.** Mass schooling standardised pace, path and assessment. ML-based modeling of learner knowledge and behavior makes individual pacing and sequencing feasible at scale. Evidence from tutoring research suggests that well-designed intelligent tutoring systems can approach the effectiveness of human tutoring on some tasks (VanLehn, 2011), and large-scale field evaluation of a cognitive-tutor mathematics curriculum reported gains in one of its two years of study (Pane et al., 2014), though effects vary by context.
2. **From periodic to continuous assessment.** Learning analytics allow ongoing, low-stakes evidence of understanding instead of occasional high-stakes examinations (Siemens and Long, 2011).
3. **From scarce to abundant content and feedback.** Generative AI makes explanations, examples and practice items nearly free, shifting scarcity to judgement: knowing what is correct, relevant and worth learning.
4. **From knowledge transmission to capability building.** When recall and routine production are cheaply automated, the educational emphasis moves toward critical thinking, problem framing, verification, collaboration and ethical reasoning.
5. **From teacher as sole expert to teacher as learning architect.** Teachers increasingly design human-AI learning activities, interpret analytics and safeguard wellbeing. Critics caution against techno-solutionism and the displacement of teachers (Selwyn, 2019), a concern this paper takes seriously.

A paradigm shift is therefore not the presence of new tools but the simultaneous change in what is taught, how it is assessed, who does what, and how decisions are governed.

## 6. PROPOSED FRAMEWORK: THE FIVE-LAYER SMART EDUCATION FRAMEWORK (FLSEF)

Most existing models either describe technology architecture or pedagogical theory, rarely both together with governance. FLSEF integrates five interdependent layers (Figure 1, described textually).

**Layer 1: Data and Infrastructure:** Connectivity, devices, learning management systems, repositories, interoperability standards and secure data stores. Design principle: collect only data that serves a defined learning purpose (data minimization) and ensure local-language and low-bandwidth accessibility.

**Layer 2: Intelligence:** The ML and AI models: predictive (risk, performance), diagnostic (knowledge tracing, misconceptions), recommender (resources, pathways), and generative (explanation, feedback, content). Design principle: choose the simplest model adequate for the purpose, and prefer explainable approaches where decisions affect students' futures.

**Layer 3: Pedagogy:** Learning design that determines how intelligence is used: mastery learning, formative feedback, inquiry, collaborative and project-based tasks, and redesigned assessment. Design principle: pedagogy leads, technology follows; every AI function must map to a learning outcome.

**Layer 4: Governance and Ethics:** Policies on privacy, consent, bias auditing, transparency, procurement, academic integrity, intellectual property and accountability. Design principle: every consequential automated recommendation must have a human reviewer and a route of appeal.

**Layer 5: Human Agency and Capability**: Teacher and student AI literacy, professional development, wellbeing, and participation of learners and educators in decisions. Design principle: AI should enlarge human judgement and relationships, not substitute for them.

**Interactions:** The layers form a loop rather than a stack. Learning outcomes and educator feedback (Layer 5) shape pedagogical design (Layer 3), which sets requirements for models (Layer 2) and data (Layer 1), all bounded by governance (Layer 4). Monitoring of outcomes feeds back into every layer. A weakness in any layer limits the whole: powerful models on poor data, or strong tools without teacher capability, produce little educational value.

**Propositions for testing:**

- P1: Institutions with balanced development across all five layers will report higher

learning gains and trust than those investing mainly in Layers 1 and 2.

- P2: Teacher AI literacy (Layer 5) moderates the effect of AI tools on student outcomes.
- P3: Explicit governance mechanisms (Layer 4) are associated with lower incidence of integrity and fairness problems.
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## 7. Institutional AI Maturity Model for Education

To make FLSEF actionable, Table 2 offers a five-level maturity model for colleges and universities.

**Table 2. AI maturity model for educational institutions (author's proposal).**

| Level | Name | Characteristics | Typical indicators |
|---|---|---|---|
| 1 | Ad hoc | Individual teachers experiment with public AI tools; no policy | No guidelines, inconsistent practice |
| 2 | Aware | Institution acknowledges AI; basic guidelines on use and integrity | Interim policy, awareness workshops |
| 3 | Structured | Approved tools, training programmes, redesigned assessments in pilot courses | Pilot evaluations, data-protection practices |
| 4 | Integrated | AI embedded in teaching, advising and administration with analytics and bias audits | Regular audits, student support analytics, curriculum change |
| 5 | Adaptive | Continuous evidence-based improvement, active participation in research and policy | Published evaluations, stakeholder governance bodies |

The model is intended for self-assessment and planning. Many public institutions will rightly begin at Levels 1 and 2; the priority at those levels is low-cost, high-value steps: clear classroom guidelines, teacher training and assessment redesign, before any large technology purchase.

## 8. DISCUSSION

### 8.1 OPPORTUNITIES:

Personalisation and support. Adaptive sequencing, instant feedback and multilingual explanation can serve first-generation learners and large classes in which individual attention is limited. Early support. Predictive analytics can flag learners at risk so that mentors can intervene, provided predictions are used to offer help rather than to label students. Teacher productivity. Drafting of materials, question banks, rubrics and routine feedback can free teacher time for mentoring. Accessibility. Speech recognition, text-to-speech, translation and captioning can lower barriers for learners with disabilities and for regional-language speakers.

### 8.2 RISKS AND CHALLENGES:

Bias and fairness: ML systems can reproduce and amplify bias in data and design (Mehrabi et al., 2021), with real consequences when used for admissions, grading or risk scoring.

Privacy and surveillance: Continuous data collection, including video and behavioural monitoring, raises consent and proportionality concerns.

Accuracy and over-reliance: Generative models can state falsehoods confidently; students may substitute AI output for their own thinking, weakening foundational skills if tasks are not redesigned.

Assessment integrity: Take-home essays and routine assignments are no longer reliable evidence of individual attainment without redesign (oral defence, process portfolios, in-class and applied tasks). Detection tools alone are not a sound basis for sanctions.

Digital divide: Benefits accrue to those with devices, bandwidth and AI literacy; without deliberate action, AI can widen existing inequalities.

Teacher agency: If tools are imposed without consultation, teachers risk deskilling and loss of professional autonomy (Selwyn, 2019).

### 8.3 THE INDIAN HIGHER-EDUCATION CONTEXT

The National Education Policy 2020 (Ministry of Education, 2020) calls for technology-enabled, flexible, learner-centered and multidisciplinary education, with attention to equity, multilingualism and teacher development. These aims align closely with what AI can support, but several conditions apply for government and rural-region colleges: reliable connectivity and devices; tools that work in Kannada and other regional languages; teacher training that is sustained rather than one-off; and data-protection safeguards consistent with national law. Regional contexts also present opportunities, such as AI-supported bridge courses for students entering from diverse school backgrounds and analytics-assisted mentoring in large undergraduate programmes (for example, BCA and BSc computer science). Institutions are advised to treat the maturity model as a staged roadmap and to begin with pilots whose outcomes are measured and shared.

### 8.4 IMPLICATIONS FOR PRACTICE AND POLICY

- **Teachers:** develop AI literacy; redesign assignments to emphasize reasoning, process and application; model critical verification of AI output.
- **Students:** use AI as a scaffold, not a substitute; disclose its use; practice evaluating and correcting AI-generated content.
- **Institutional leaders:** adopt written policies; prefer tools with transparent data practices; invest in training before technology.
- **Policy makers:** fund infrastructure and regional-language resources; require evaluation and transparency from vendors; protect student data (UNESCO, 2021).

## 9. FUTURE RESEARCH DIRECTIONS

1. Empirical validation of FLSEF and the maturity model through multi-institution case studies and surveys using structural equation modeling.
2. Randomized or quasi-experimental trials of generative AI tutors on learning outcomes, retention and transfer, across disciplines and languages.
3. Longitudinal studies of effects on critical thinking, writing and self-regulation.
4. Fairness auditing of educational prediction models in Indian demographic and language contexts.
5. Explainable and privacy-preserving learning analytics, including federated learning across institutions.
6. Assessment innovation: valid and scalable alternatives to take-home written work.
7. Teacher professional development models and their effect on classroom practice.
8. Cost-effectiveness analyses for resource-constrained public institutions.

## 10. LIMITATIONS

This is a conceptual, narrative review; it does not report primary empirical data, and its selection of literature, though purposive, cannot be exhaustive. The field changes rapidly, so specific tools and capabilities discussed may be superseded. The framework and maturity model are theoretical proposals that require empirical testing and refinement.

## 11. CONCLUSION

The evolution of AI and ML, from symbolic rules to statistical learning, deep neural networks and generative foundation models, has progressively moved intelligence closer to the learner and the classroom. Their convergence with education is a paradigm shift because it changes simultaneously the assumptions about personalization, assessment, content scarcity, curricular emphasis and the teacher's role. The Five-Layer Smart Education Framework and the institutional maturity model proposed here offer a structured way to move from scattered experimentation to responsible, evidence-based adoption. The decisive factor will not be the sophistication of algorithms but the quality of pedagogy, the strength of governance and the capability and agency of educators and learners. Smart education, properly understood, is not education delivered by machines but education made wiser by them.

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