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An Analytical Study of the Role of Artificial Intelligence in Individualized Learning and Student Participation in India

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Abstract - Artificial intelligence (AI) is increasingly proposed to deliver individualized learning at scale, yet evidence from India, where classrooms are large, heterogeneous and unevenly digitized, is fragmented and rarely examines student participation as the mechanism linking AI to learning. This study applies an integrative review design to (i) international and Indian research on AI-enabled individualized learning and student engagement, (ii) India's policy and platform ecosystem, and (iii) official school digital-infrastructure indicators from the Unified District Information System for Education Plus (UDISE+) for 2022-23 to 2024-25. A conceptual framework linking AI affordances, individualization mechanisms and the behavioral, emotional and cognitive dimensions of engagement is developed, and five testable propositions are derived. The findings indicate that intelligent tutoring and adaptive systems yield moderate-to-large learning gains in controlled studies and that Indian experimental evidence is encouraging. Readiness, however, is sharply uneven: computer and internet facilities were reported in 64.7% and 63.5% of schools in 2024-25, and only 34% of government schools with Classes VI and above reported ICT labs. Infrastructure, teacher capacity, vernacular content, data governance and equity safeguards emerge as binding constraints. The study contributes a participation-centered framework, a state-level readiness diagnosis and a staged policy and research agenda. Because it relies on secondary evidence, the propositions require empirical testing.

Keywords: artificial intelligence in education; individualized learning; adaptive learning; student engagement; digital divide; India; NEP 2020

1. INTRODUCTION

India has the 2nd largest school system in the world after the United States of America and over 1.47 million schools are registered under UDISE+ in 2024-25 [1]. Prior knowledge, language, lesson pace and motivation vary widely among learners within a single classroom, and the Annual Status of Education Report (ASER) repeatedly shows that fundamental reading and arithmetic skills are not evenly distributed across grades – a lesson pace based on a textbook doesn't work very well for many children [2]. Individualized learning – where content, pace, feedback and support are tailored to the individual – has been offered as a cure for a long time. The vision of tutoring one student at a time by another student with similar results was validated by Bloom's demonstration that by two standard deviations [3] one-to-one tutoring was more effective than traditional group instruction, but human tutoring is labor intensive and difficult to scale. This has renewed the promise of individualization at scale with the advances of machine learning, learning analytics and, more recently, generative language models [4, 5]. Integration of technology, adaptive assessment, and personalized learning pathways are mentioned in the National Education Policy (NEP) 2020 [6] and education is identified as a priority sector in the national AI strategy [7] of India. On a global level, however, it is important to highlight that the utility of e-learning technologies relies on the terms and conditions under which they are deployed, bringing this to the attention of the community [8]. The conditions in which policy is executed are as powerful as policy ambition. There are three gaps that inspire this paper.

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First, most of the literature on AI in education comes from high income and high connectivity environments and is rarely studied for its application to India [9, 10]. Second, the studies focus either on learning outcomes or technology adoption and rarely address student participation, or student behaviour, emotional states and cognition as the link between the two [11]. Thirdly, there is little evidence of effectiveness being read alongside evidence on infrastructure readiness, while evidence on effectiveness is of little use to learners who do not have access to the technology. This study thus seeks answers to three research questions:

- **RQ1.** What does existing evidence say about the effect of AI-enabled individualization on learning and student participation?
- **RQ2.** How is India's policy and platform ecosystem positioned to deliver individualized AI-supported learning?
- **RQ3.** How ready is India's school infrastructure for such delivery, and which constraints matter most?

The paper makes three contributions:

- A participation-centered conceptual framework, with five testable propositions, linking AI affordances to individualization and learning outcomes.
- A synthesis of international and Indian evidence on AI-enabled individualized learning, together with a map of India's policy and platform ecosystem.
- A state-level readiness diagnosis using official UDISE+ indicators for 2022-23 to 2024-25, and a staged policy and research agenda.

2. LITERATURE REVIEW AND RESEARCH GAP

2.1 AI and individualized learning

Individualized learning is about modifying content, speed, content progression, and/or support for the learner. The rationale behind it goes back a long way: Bloom reported that tutored students achieve about two standard deviations more than traditionally taught students, and the notion of task difficulty matching students' current ability (Section 3) is supported by the concept of the "zone of proximal development." There's a way to approximate this at scale with AI. The most frequently evaluated type is the intelligent tutoring system (ITS) ,a meta-study of 50 controlled evaluations showed a median effect size of 0.66 standard deviations compared to conventional instruction [12] and step learning ITS were found to be as effective as human tutors [13]. However, reviews on personalized learning have noted that the word is defined in a loose and nonspecific way, and that the effects are dependent on what is personalized, how, and for what purpose [14], as well as a large US study which reported positive but small and somewhat mixed outcomes based on implementation quality [15]. There is also a wider synthesis that connects AI applications to learner profiling, adaptive systems, assessment and feedback, and administration, while highlighting the lack of representation of pedagogical and ethical perspectives and the role of the educators. The results of the online higher education show systematic evidence for the domination of performance prediction, resource recommendation and automated assessment [17]. These capabilities are extended by generative AI to conversational, on-demand explanation, but with issues of accuracy raised and bias and over-reliance [5]. The failure of poorly designed tutoring system may also be because it does not consider the human context in which it functions [19]. Selected studies are summarized in Table 1.

Table 1. Summary of selected prior studies on AI-enabled individualized learning

Study	Context	AI / adaptive approach	Key finding
Kulik and Fletcher [12]	Meta-analysis of 50 controlled evaluations	Intelligent tutoring systems	Median effect size of about 0.66 SD over conventional instruction

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Study	Context	AI / adaptive approach	Key finding
VanLehn [13]	Review of tutoring studies	Step-based tutoring systems	Effects (about 0.76 SD) comparable to human tutoring (about 0.79 SD)
Bernacki et al. [14]	Systematic review of personalized learning research	Personalized learning designs of varied kinds	Definitions and designs vary widely; effects depend on what is personalized and how
Pane et al. [15]	Quasi-experimental study, US schools	Personalized learning initiatives	Positive but modest effects with wide variation across schools
Zawacki-Richter et al. [9]	Systematic review of 146 articles, 2007–2018, higher education	Profiling, assessment, adaptive systems, ITS	Limited educator involvement and weak ethical reflection
Bond et al. [10]	Meta systematic review, higher education	AI applications across reviews	Calls for greater ethical reflection, collaboration and methodological rigour
Muralidharan et al. [20]	Randomized evaluation, Delhi, Grades 6–9	Mindspark adaptive software	Gains of about 0.36 SD in mathematics and 0.22 SD in Hindi in roughly 4.5 months
Chen et al. [16]	Literature review	AI in administration, instruction and learning	Personalization is a major and growing application area
Ouyang et al. [17]	Systematic review, online higher education, 2011–2020	Performance prediction, recommendation, automated assessment	Many studies report gains in performance and engagement; designs are often quasi-experimental
Kasneci et al. [5]	Conceptual review	Large language models	Opportunities for personalized support; risks of bias, over-reliance and reduced critical thinking

Source: Compiled by the author from [5], [9], [10], [12]–[17] and [20].

2.2 Student participation and engagement

Student engagement is generally defined as a multidimensional construct that includes behavioral (attending, trying hard, persevering), emotional (interest, belonging and anxiety), and cognitive (self-regulation, strategies used) dimensions [11]. In addition, according to S. D. T. [21] learning environments should foster competence, autonomy, and relatedness to sustain engagement. This is important for AI studies because there are more measurable behaviors (like clicks, time spent on task), but less measurable emotional and cognitive engagement. Some scholars argue that personalization through data could de-skill teaching and learning, potentially limiting learning to what is measurable and thus reducing agency given to teachers and learners [22, 23]. The literature on human-AI complementarity

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highlights how AI can be used to complement, not replace, teacher professional judgement, such as in continuously monitoring and managing a classroom in real-time with a classroom orchestration dashboard [24].

2.3 The Indian evidence base

India presents a unique test case. Randomized experiments indicate that instruction at the right level, not grade level, can increase learning: learning gains were evident for remedial and computer-assisted programmes in Mumbai and Vadodara [25] and the Teaching at the Right Level approach was then scaled up via the government system [26]. The most stringent evidence of adaptive software comes from a randomized study of Mind spark in Delhi that measured significant improvements in mathematics and Hindi after a couple of months of use [20]. In addition to these studies, the Indian literature is mostly comprised of small scale case studies, platform reports and policy documents and seldom measures participation directly. The presence of wide within-grade variation in basic skills in the ASER results reinforce the need for individualization on the one hand, and the need to balance innovation with inclusion, teacher capacity with data protection in national strategies, on the other [2, 27].

2.4 Research gap

Taken together, the literature shows (i) robust but context-bound effectiveness evidence for adaptive systems [12, 13, 20], (ii) limited direct measurement of emotional and cognitive participation [11, 14], and (iii) scant Indian evidence beyond a small number of rigorous evaluations [20, 25, 26]. The studies reviewed do not link AI-enabled individualization, participation and national readiness indicators in the Indian school context; this paper addresses that gap.

3. CONCEPTUAL FRAMEWORK

3.1 Theoretical anchors and framework

The framework is grounded in three ideas. First, Vygotsky's zone of proximal development [28] suggests that learning is most effective when tasks are set just above the learner's current level of competence but at a level he can handle if he is supported by a learner model and a helpful sequencing of the tasks. Second, self-determination theory [21] proposes that perceived competence, autonomy and relatedness are correlated with persistent participation, suggesting that tasks that are well-designed and feedback provided in a timely manner can increase emotional and behavioral involvement. Third, a partnership approach towards AI in education [29] reinforces the vision that AI serves to augment educators, not replace them, and encourages the capacity of educators as a moderator. The framework in Figure 1 suggests that the individualization mechanisms (pace, path, difficulty, language and feedback) are supported by the AI affordances (learner modelling, adaptive sequencing, automated feedback, conversational support and analytics). Such mechanisms have an impact on behavioural, emotional and cognitive participation, which subsequently determines learning outcomes. Three contextual conditions (digital infrastructure, teacher capacity, and policy and data governance) moderate the pathway. Table 2 relates the affordances to the mechanisms and the participation dimensions.

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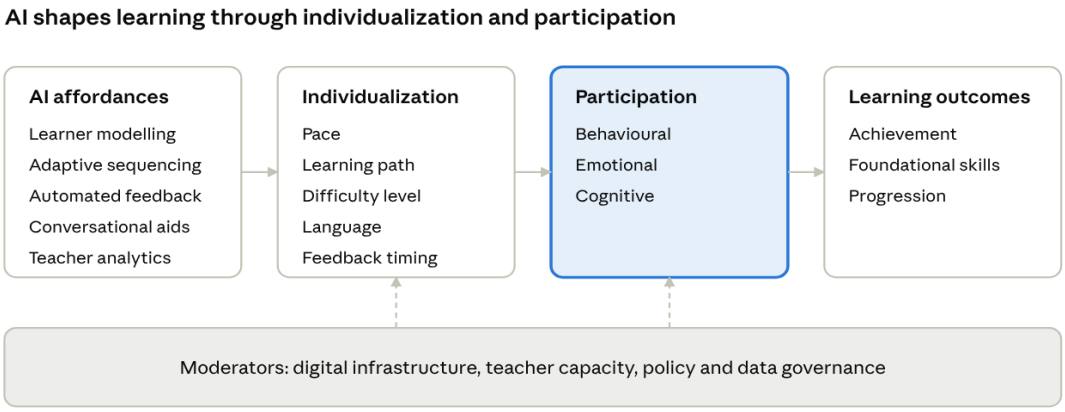


Figure 1. Conceptual framework linking AI affordances, individualization, student participation and learning outcomes

Source: Author's conceptual framework, synthesized from [4], [11], [21], [28] and [29].

Table 2. Mapping of AI affordances to individualization mechanisms and participation dimensions

AI affordance	Individualization mechanism	Behavioural participation	Emotional participation	Cognitive participation
Learner modelling and diagnostics	Starting point matched to prior knowledge	Regular, goal-directed practice	Reduced frustration from mismatched tasks	Targeted remediation of misconceptions
Adaptive sequencing	Pace and path adjusted to mastery	Sustained time on task	Sense of competence	Scaffolded progression
Automated, immediate feedback	Step-level hints and corrections	More attempts and revisions	Lower fear of public error	Metacognitive monitoring
Conversational and language support	Explanations in the learner's language and register	Willingness to ask questions	Inclusion of vernacular learners	Deeper conceptual explanation
Learning analytics for teachers	Teacher intervention targeted to at-risk learners	Early detection of disengagement	Timely human support	Informed instructional decisions

Source: Developed by the author on the basis of [4], [5], [11] and [29].

The operational logic is a closed adaptive loop, shown in Figure 2: learner interaction data updates a learner model, the model drives content selection, feedback generates new interaction data, and aggregated analytics inform teacher action.

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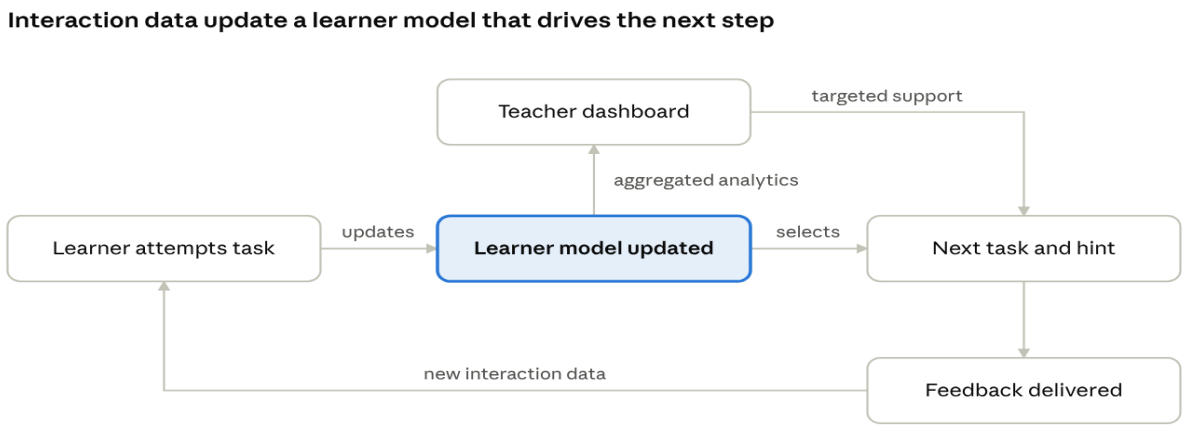


Figure 2. Adaptive learning cycle in AI-supported individualized instruction

Source: Author's schematic, adapted from the adaptive tutoring architecture discussed in [4] and [13].

3.2 Propositions

From the framework, five propositions are derived for empirical testing in subsequent research:

- **P1.** Greater use of adaptive sequencing and diagnostics is associated with higher behavioral participation (persistence and time on task).
- **P2.** Immediate, step-level feedback is associated with higher emotional participation (lower anxiety, greater perceived competence).
- **P3.** Language-supportive and conversational features increase the participation of vernacular-medium and first-generation learners disproportionately.
- **P4.** The effect of AI-enabled individualization on learning outcomes is mediated by behavioral, emotional and cognitive participation.
- **P5.** Digital infrastructure, teacher capacity and data governance moderate the strength of the relationships in P1 to P4.

4. METHODOLOGY

4.1 Research design

An integrative review design [30] was adopted because the aim is to synthesize heterogeneous evidence (experimental studies, systematic reviews, conceptual work, policy texts and administrative statistics) into a framework, rather than to estimate a pooled effect. The study is analytical and conceptual, supported by secondary quantitative indicators, and it was not registered as a systematic review.

4.2 Sources and selection

Three evidence streams were used. First, peer-reviewed literature on AI, individualized or personalized learning and engagement was reviewed, giving priority to Scopus-indexed journals and widely cited syntheses, and to randomized or quasi-experimental evaluations, systematic reviews and meta-analyses. Second, policy documents, namely NEP 2020 [6], the national AI strategy [7] and UNESCO guidance [27], were examined for their treatment of personalization and technology. Third, school-level digital-infrastructure indicators for 2022-23 to 2024-25 were drawn from official UDISE+ data tabulated in Ministry of Education replies to the Lok Sabha [1, 31]. Sources were included if they were:

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- relevant to AI or adaptive systems in relation to individualization, personalization or engagement;
- peer-reviewed, or an official government or intergovernmental publication;
- written in English and available in full text.

Commercial claims without independent evaluation and opinion pieces without an evidence base were excluded from the evidence synthesis.

4.3 Analysis

The literature was coded against the framework dimensions (affordances, individualization mechanisms, participation dimensions and moderators) using the logic of reflexive thematic analysis [32]. Infrastructure indicators were analysed descriptively: the percentage of schools reporting computer facilities, the percentage reporting internet facilities, and the percentage of government schools with Classes VI and above reporting ICT labs. Percentage-point changes were calculated by the author, and states were selected to illustrate the range of variation (highest, lowest and mixed profiles). “Computer facility” denotes availability as reported in UDISE+ and does not guarantee that equipment is functional or used for teaching. The study used only published, aggregated data and involved no human participants.

5. ANALYSIS AND FINDINGS

5.1 Policy and platform ecosystem (RQ2)

India’s ecosystem combines public digital infrastructure, private adaptive platforms and curricular initiatives (Table 3). NEP 2020 devotes a full chapter to technology use and integration and endorses adaptive assessment and personalized pathways [6]. Public platforms mainly provide content, multilingual access and administrative data, whereas deeper adaptive functionality, such as that evaluated experimentally by Muralidharan et al. [20], has largely been delivered by private providers. This suggests that the personalization potential of public platforms is currently under-exploited, particularly with respect to real-time learner modelling.

Table 3. Selected AI-relevant initiatives and platforms in Indian education

Initiative	**Lead agency / provider**	**Relevant AI or adaptive feature**	**Relevance to individualization and participation**
DIKSHA	Ministry of Education / NCERT	Digital content and teacher resources; usage analytics	Content access across languages; analytics base for personalization
SWAYAM	Ministry of Education and partner bodies	Online courses with assessments	Self-paced learning for older learners
BHASHINI	Ministry of Electronics and IT	Language translation and speech technologies	Vernacular access and inclusion
Vidya Samiksha Kendras	State education departments under Samagra Shiksha	Data aggregation and monitoring dashboards	Early identification of disengagement and learning gaps
Mindspark	Educational Initiatives (private)	Adaptive mathematics and language software	Experimentally evaluated gains [20]
Embibe	Private provider	AI-based diagnostics and recommendations	Personalized practice and test preparation
CBSE AI	Central Board of	AI offered as a skill or	Builds learner and teacher AI

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Initiative	Lead agency / provider	Relevant AI or adaptive feature	Relevance to individualization and participation
subject	Secondary Education	elective subject	literacy

Source: Compiled by the author from [6], [20] and publicly available programme descriptions; features vary by programme and over time.

5.2 Infrastructure readiness (RQ3)

National indicators have improved steadily (Table 4; Figure 3). The share of schools reporting computer facilities rose from 47.7% in 2022-23 to 64.7% in 2024-25, and internet facilities from 49.7% to 63.5% over the same period [1]. These gains are substantial, yet roughly one in three schools still lacks either facility, which limits the reach of any AI-based individualization that depends on devices and connectivity.

Table 4. Percentage of schools with computer and internet facilities in India, 2022-23 to 2024-25

Indicator	2022-23	2023-24	2024-25	Change 2022-23 to 2024-25 (percentage points)
Computer facility (%)	47.7	57.2	64.7	+17.0
Internet facility (%)	49.7	53.9	63.5	+13.8

Source: Ministry of Education [1], based on UDISE+; change calculated by the author.

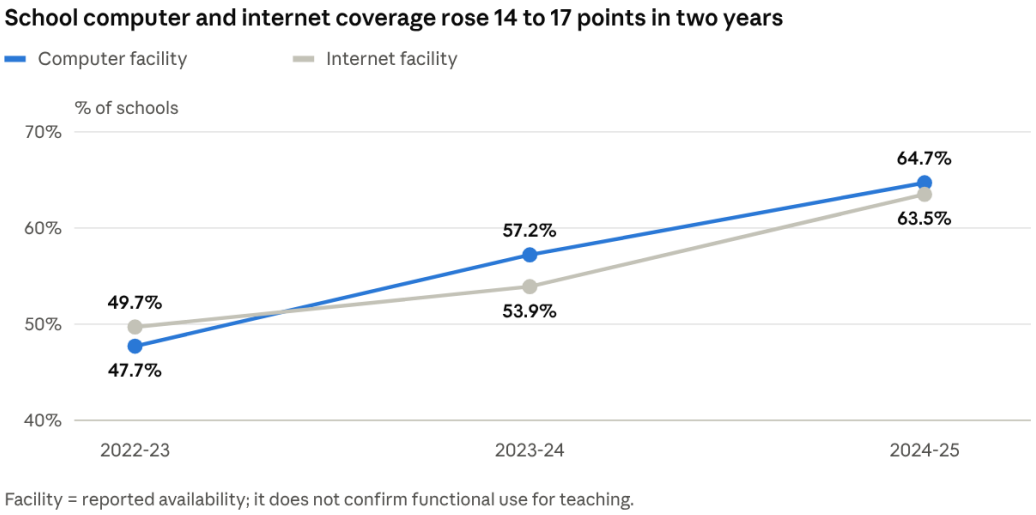


Figure 3. Trend in computer and internet facilities in Indian schools, 2022-23 to 2024-25 (% of schools)

Source: Plotted by the author from Ministry of Education [1], based on UDISE+ data.

The national averages conceal wide state-level variation (Table 5). Delhi reports near-universal computer and internet coverage, whereas West Bengal reports internet facilities in only 18.6% of schools and Arunachal Pradesh in 33.6%. Bihar illustrates a different pattern: internet facilities are reported in 84.8% of schools, but computers in only 25.2%, so connectivity exists without devices. Such asymmetries imply that state-specific sequencing of investment, rather than a uniform national rollout, is needed.

Table 5. Percentage of schools with computer and internet facilities in selected states and UTs, 2024-25

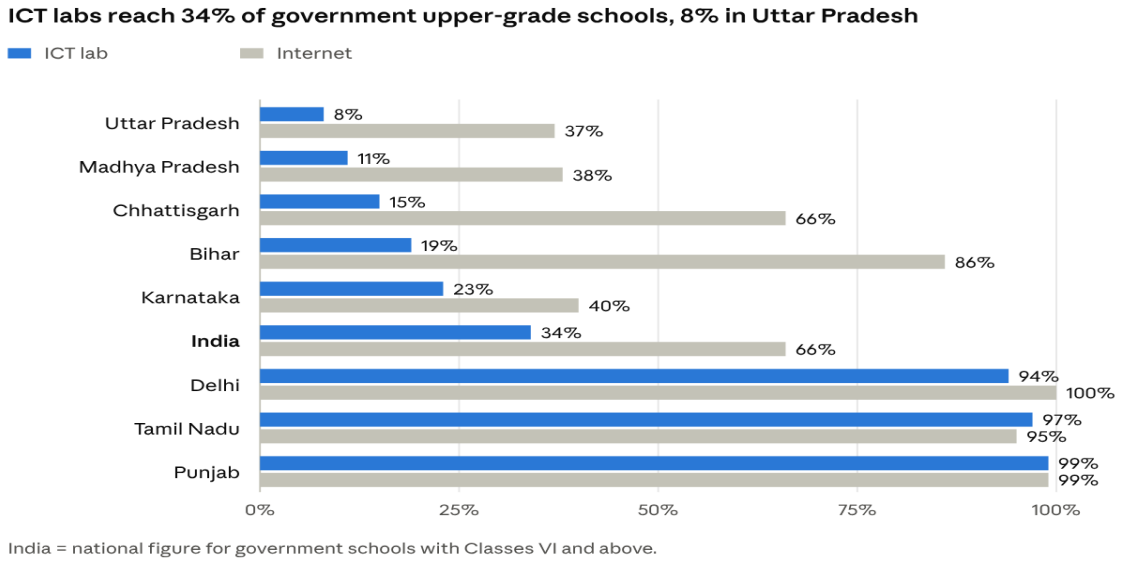
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State / UT	Computer facility (%)	Internet facility (%)
Delhi	99.9	100.0
Andhra Pradesh	79.6	99.0
Assam	78.7	87.2
Chhattisgarh	62.7	64.3
Arunachal Pradesh	47.7	33.6
Bihar	25.2	84.8
West Bengal	25.1	18.6
India	**64.7**	**63.5**

Source: Ministry of Education [1], based on UDISE+ 2024-25; selection of states by the author to illustrate the range of variation.

The position in government schools offering Classes VI and above, where subject-level adaptive software is most relevant, is weaker still (Figure 4). Only 34% of such schools reported ICT labs nationally, compared with 66% reporting internet access [31]. Uttar Pradesh (8%) and Madhya Pradesh (11%) report particularly low lab availability, while Tamil Nadu (97%) and Punjab (99%) report near-universal availability. For a school system in which government schools serve most children, this gap defines the practical ceiling of AI-enabled individualization in the near term.



UDISE+ via Lok Sabha Q. 1561 · 9 states/India, 2024-25

Figure 4. ICT lab and internet availability in government schools with Classes VI and above, selected states, 2024-25 (% of schools)

Source: Plotted by the author from Ministry of Education [31], based on UDISE+ 2024-25.

5.3 Synthesis of evidence on participation (RQ1)

The reviewed studies all find that adaptive and tutoring systems are linked to learning gains [12, 13, 20] and the framework implies that participation is the mediating variable: tasks are designed well to maintain effort, feedback is

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immediate to reduce the costs of error, and language support helps to expand participation. (Table 2) However, direct measurement of emotional and cognitive involvement is not frequently found in the literature researched, and most studies assume the level of participation based on behavioral artifacts [11, 14, 17]. Based on the available evidence, however, it is possible to draw a cautious conclusion: AIEI has the potential to improve outcomes and behavioral participation under appropriate implementation conditions, with less evidence on the effects of AIEI on deeper engagement, particularly in the context of Indian public schools.

5.4 Summary of key findings

The analysis yields six principal findings.

1. **Effectiveness evidence is strong but narrow.** Controlled studies document learning gains from structured adaptive and tutoring systems [12, 13, 20], mainly in mathematics and language and in settings with consistent use; effects are context-bound [14, 15].
2. **Participation is the plausible mechanism but is rarely measured.** Most studies infer engagement from behavioural traces, leaving emotional and cognitive engagement under-tested (Section 5.3).
3. **Public platforms lead on content and access, not on adaptivity.** India's public platforms emphasize content, language access and data, while deep adaptive functionality is largely private (Table 3).
4. **Infrastructure has improved but remains incomplete.** Computer facilities rose from 47.7% to 64.7% and internet facilities from 49.7% to 63.5% between 2022-23 and 2024-25 (Table 4).
5. **State disparities are large and asymmetrical.** West Bengal reports internet in 18.6% of schools, while Bihar reports internet in 84.8% but computers in only 25.2% (Table 5).
6. **Government upper-grade schools are least ready.** ICT labs are reported by 34% of such schools nationally, 8% in Uttar Pradesh and 11% in Madhya Pradesh, against 97% in Tamil Nadu and 99% in Punjab (Figure 4).

Together, these findings suggest that the near-term constraint on AI-enabled individualization in India is the system's capacity to deliver it, namely devices, connectivity, functioning labs and trained teachers, rather than the sophistication of algorithms. Without targeted action, the benefits are likely to accrue first to better-resourced schools and states.

6. DISCUSSION

6.1 Interpretation of the findings

Three implications follow. First, the Indian evidence from experimentation reveals the possibility of teaching children at their level, which is possible and effective, but it is in a specific programme, in a specific setting and should not be extrapolated to all AI programmes and settings. Second, the readiness indicators reveal that devices, connectivity and working labs are the limiting factor in many states, not algorithms. The policy challenge is that individualisation through AI can be beneficial for already privileged schools, but it could also widen learning gaps, thus creating a policy risk. Third, the participation lens brings to light questions the outcome metrics fail to capture: of how systems emotionally involve learners, how they empower learners, and how they work in the language(s) used by the learners.

6.2 Theoretical contribution

The study extends the individualized-learning literature by positioning participation as the explicit mediating mechanism between AI affordances and learning outcomes, and by treating infrastructure, teacher capacity and governance as moderators rather than background conditions. Propositions P1 to P5 convert this into testable form and respond to calls for more rigorous, ethically aware and educator-involving research [9, 10, 18].

6.3 Teachers, ethics and governance

Teachers play a pivotal role: analytics are only effective when teachers have the time, training and authority to make use of them, as suggested by evidence of teacher–AI complementarity [24] and criticism against the use of technology to replace professional judgement [19, 22]. On-demand support and safeguarding around accuracy, bias and academic

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integrity are more possible with Generative AI [5]. Ethical issues like privacy, bias and transparency are well documented in K-12 environment [33] and India's Digital Personal Data Protection Act, 2023 also puts responsibility on processing of children's PDP, including seeking consent from parents [34]. Thus, tools that will be used in schools will have to be designed to comply from the beginning. Table 6 presents stakeholder main constraints and enabling responses organized by stakeholder.

Table 6. Key constraints and enabling responses for AI-supported individualized learning in India

Domain	Constraint	Enabling response	Primary stakeholder
Infrastructure	Uneven devices and connectivity across states and school types	State-specific investment sequencing; shared labs, low-bandwidth and offline-capable tools	Central and state governments
Teacher capacity	Limited training in using learner analytics and AI tools	Pre-service and in-service training; teachers kept in the decision loop	Teacher education institutions, state education departments
Content and language	Scarcity of quality adaptive content in Indian languages	Public investment in multilingual content and language technologies	Ministry of Education, MeitY, publishers
Data governance	Student data privacy and algorithmic bias risks	Clear data-protection rules, audits and transparency for school-facing tools	Regulators, platform providers
Evidence	Few rigorous evaluations that measure participation	Pilots with randomized or quasi-experimental designs and engagement measures	Researchers, funders, state governments
Equity	Risk that benefits accrue to better-resourced schools	Targeting of first-phase deployment to low-readiness districts, with monitoring	Policy-makers, civil society

Source: Synthesized by the author from Sections 2 to 5, with reference to [1], [5], [22], [27], [31], [33] and [34].

7. POLICY AND PRACTICAL IMPLICATIONS

The analysis supports a staged agenda, summarized below by time horizon.

Short term (0–2 years)

- Prioritize functional devices, connectivity and offline-capable tools in low-readiness states, using existing public platforms as the delivery channel.
- Audit the functionality, not only the availability, of computers and labs, and publish usage indicators.
- Begin teacher training on interpreting learner analytics and on safe use of generative AI.

Medium term (2–5 years)

- Add learner modelling and teacher dashboards to public platforms, with multilingual support through national language technologies.
- Design pilots as evaluations from the outset, measuring behavioural, emotional and cognitive participation alongside learning outcomes, and plan for scale-up from the start [26].

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- Target first-phase deployment at low-readiness districts, with equity monitoring.

Long term (5 years and beyond)

- Require transparency, data-protection compliance and bias audits in the procurement and regulation of AI tools used in schools [27, 34].
- Treating teacher professional development as a core component of every deployment rather than an add-on.
- Build national evidence repositories on what works, for whom and at what cost.

8. LIMITATIONS

The findings should be read considering the following limitations, which also indicate where confidence in the conclusions is weaker.

- **Secondly, only.** No primary data were collected, so the framework and propositions P1 to P5 remain untested empirically.
- **Review design.** An integrative review was used rather than a registered systematic review; selection may therefore be affected by publication and language bias, and Indian grey literature is only partly covered.
- **Indicator limitations.** UDISE+ indicators describe school-reported availability of facilities, not their functionality, frequency of use or student-level and household access. Only three years of data are used, and the states shown illustrate variation rather than representing all states.
- **Readiness as a proxy.** Infrastructure indicators measure the preconditions for AI use, not AI use itself or its effects on participation.
- **Transferability of effect sizes.** Effect sizes come from specific settings (for example, after-school centres in Delhi, or US and higher-education contexts) and may not transfer to other Indian school contexts [14, 15, 20].
- **Platform descriptions.** Programme features in Table 3 are indicative, change over time, and for most platforms lack independent evaluation.
- **Participation inferred.** Emotional and cognitive participation are inferred conceptually, because most of the reviewed studies did not measure them directly [11, 17].

These limitations temper, but do not negate, the central conclusion that readiness and implementation conditions, rather than algorithms alone, will determine whether AI-enabled individualization reaches Indian learners equitably.

9. FUTURE SCOPE

The limitations point to a research agenda that moves from conceptual synthesis to empirical testing. The most valuable next steps combine robust causal designs with direct measurement of participation and with attention to equity and governance.

- **Test the propositions.** Use student and teacher surveys and structural equation or mediation models to test P1 to P5 across states with contrasting readiness profiles.
- **Evaluation in government schools.** Conduct randomized or stepped-wedge evaluations of adaptive and generative AI tools, with validated behavioral, emotional and cognitive engagement instruments alongside learning outcomes, and with cost-effectiveness analysis [26].
- **Follow engagement over time.** Use longitudinal and learning-analytics studies to trace engagement trajectories and the persistence of gains after initial novelty.
- **Vernacular and multilingual AI.** Examine accuracy, bias and learning effects of generative AI in Indian languages, particularly for first-generation and rural learners.
- **Teacher–AI complementarity.** Co-design and test dashboards and workflows that keep teachers in the decision loop and study their effect on teacher workload [24].
- **Equity and governance.** Audit algorithmic bias across gender, region, language and disability, and study compliance with data-protection obligations for children’s data [34].
- **Functional readiness.** Link UDISE+ indicators with usage logs, district-level data and household access to move from availability to functional readiness.

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- **Scale-up and comparison.** Study how successful pilots scale through public systems [26] and compare experience with other emerging economies.

10. CONCLUSION

AI offers a credible route to individualized learning, and the available evidence, including experimental evidence from India, indicates meaningful gains in learning and behavioral participation when systems are well designed and consistently used. India's policy intent is supportive, but infrastructure readiness remains uneven: while computer and internet coverage has improved markedly since 2022-23, roughly one in three schools still lacks either facility, or government schools with upper grades report limited ICT labs. Realizing the promise of AI for individualized learning and participation will therefore depend less on algorithmic sophistication than on state-specific infrastructure, teacher capacity, vernacular content, data governance and rigorous evaluation. The proposed participation-centered framework and its five propositions offer a basis for empirical work that treats participation as the mechanism through which AI influences learning.

Declarations

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Conflict of Interest: The corresponding author, Pravin Kumar Vishwakarma, the Second Author Dr. Sidhdheshwar Mishra and the Third author, Ritesh Kumar, declare that they have no conflict of interest.

Ethics: The study used only published, aggregate, and publicly available data and did not involve human participants. Therefore, ethical approval was not required.

Data Availability: All data analyzed in this study were obtained from publicly available sources cited in the manuscript.

Declaration of Generative AI Use: The authors declare that any use of generative AI tools in preparing this manuscript, if applicable, has been disclosed in accordance with the target journal's policy

REFERENCES

[1] Ministry of Education, 2026. Lok Sabha Unstarred Question No. 447 (answered 02.02.2026): Annexure on UDISE+ computer and internet facilities, 2022-23 to 2024-25. Government of India, New Delhi. https://www.education.gov.in/sites/upload_files/mhrd/files/parliament_annexure_en/447_parl.pdf

[2] ASER Centre, 2024. *Annual Status of Education Report (Rural) 2023: Beyond Basics*. ASER Centre, New Delhi.

[3] Bloom, B.S., 1984. The 2 sigma problem: the search for methods of group instruction as effective as one-to-one tutoring. *Educ. Res.* 13 (6), 4–16. https://doi.org/10.3102/0013189X013006004

[4] Holmes, W., Bialik, M., Fadel, C., 2019. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Center for Curriculum Redesign, Boston, MA.

[5] Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., et al., 2023. ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.* 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

[6] Ministry of Human Resource Development, 2020. *National Education Policy 2020*. Government of India, New Delhi.

[7] NITI Aayog, 2018. *National Strategy for Artificial Intelligence: #AIforAll*. Government of India, New Delhi.

[8] UNESCO, 2023. *Global Education Monitoring Report 2023: Technology in Education – A Tool on Whose Terms?* UNESCO, Paris. https://doi.org/10.54676/UZQV8501

[9] Zawacki-Richter, O., Marín, V.I., Bond, M., Gouverneur, F., 2019. Systematic review of research on artificial intelligence applications in higher education – where are the educators? *Int. J. Educ. Technol. High. Educ.* 16, 39. https://doi.org/10.1186/s41239-019-0171-0

[10] Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., et al., 2024. A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour. *Int. J. Educ. Technol. High. Educ.* 21, 4. https://doi.org/10.1186/s41239-023-00436-z

[11] Fredricks, J.A., Blumenfeld, P.C., Paris, A.H., 2004. School engagement: potential of the concept, state of the evidence. *Rev. Educ. Res.* 74 (1), 59–109. https://doi.org/10.3102/00346543074001059

[12] Kulik, J.A., Fletcher, J.D., 2016. Effectiveness of intelligent tutoring systems: a meta-analytic review. *Rev. Educ. Res.* 86 (1), 42–78. https://doi.org/10.3102/0034654315581420

[13] VanLehn, K., 2011. The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educ. Psychol.* 46 (4), 197–221. https://doi.org/10.1080/00461520.2011.611369

[14] Bernacki, M.L., Greene, M.J., Lobczowski, N.G., 2021. A systematic review of research on personalized learning: personalized by whom, to what, how, and for what purpose(s)? *Educ. Psychol. Rev.* 33, 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

[15] Pane, J.F., Steiner, E.D., Baird, M.D., Hamilton, L.S., Pane, J.D., 2017. *Informing Progress: Insights on Personalized Learning Implementation and Effects*. RAND Corporation, Santa Monica, CA.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

[16] Chen, L., Chen, P., Lin, Z., 2020. Artificial intelligence in education: a review. *IEEE Access* 8, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

[17] Ouyang, F., Zheng, L., Jiao, P., 2022. Artificial intelligence in online higher education: a systematic review of empirical research from 2011 to 2020. *Educ. Inf. Technol.* 27, 7893–7925. https://doi.org/10.1007/s10639-022-10925-9

[18] Hwang, G.-J., Xie, H., Wah, B.W., Gašević, D., 2020. Vision, challenges, roles and research issues of artificial intelligence in education. *Comput. Educ.: Artif. Intell.* 1, 100001. https://doi.org/10.1016/j.caeai.2020.100001

[19] Baker, R.S., 2016. Stupid tutoring systems, intelligent humans. *Int. J. Artif. Intell. Educ.* 26 (2), 600–614. https://doi.org/10.1007/s40593-016-0105-0

[20] Muralidharan, K., Singh, A., Ganimian, A.J., 2019. Disrupting education? Experimental evidence on technology-aided instruction in India. *Am. Econ. Rev.* 109 (4), 1426–1460. https://doi.org/10.1257/aer.20171112

[21] Ryan, R.M., Deci, E.L., 2000. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *Am. Psychol.* 55 (1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

[22] Selwyn, N., 2019. *Should Robots Replace Teachers? AI and the Future of Education*. Polity Press, Cambridge.

[23] Williamson, B., Eynon, R., 2020. Historical threads, missing links, and future directions in AI in education. *Learn. Media Technol.* 45 (3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

[24] Holstein, K., McLaren, B.M., Aleven, V., 2019. Co-designing a real-time classroom orchestration tool to support teacher–AI complementarity. *J. Learn. Anal.* 6 (2), 27–52. https://doi.org/10.18608/jla.2019.62.3

[25] Banerjee, A.V., Cole, S., Duflo, E., Linden, L., 2007. Remedying education: evidence from two randomized experiments in India. *Q. J. Econ.* 122 (3), 1235–1264. https://doi.org/10.1162/qjec.122.3.1235

[26] Banerjee, A., Banerji, R., Berry, J., Duflo, E., Kannan, H., Mukerji, S., S., Shotland, M., Walton, M., 2017. From proof of concept to scalable policies: challenges and solutions, with an application. *J. Econ. Perspect.* 31 (4), 73–102. https://doi.org/10.1257/jep.31.4.73

[27] Miao, F., Holmes, W., Huang, R., Zhang, H., 2021. *AI and Education: Guidance for Policy-Makers*. UNESCO, Paris.

[28] Vygotsky, L.S., 1978. *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press, Cambridge, MA.

[29] Luckin, R., Holmes, W., Griffiths, M., Forcier, L.B., 2016. *Intelligence Unleashed: An Argument for AI in Education*. Pearson, London.

[30] Snyder, H., 2019. Literature review as a research methodology: an overview and guidelines. *J. Bus. Res.* 104, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

[31] Ministry of Education, 2026. Lok Sabha Unstarred Question No. 1561 (answered 09.02.2026): Functional computer labs and internet in government schools. Government of India, New Delhi. https://www.education.gov.in/sites/upload_files/mhrd/files/parliament_annexure_en/1561_en.pdf

[32] Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. *Qual. Res. Psychol.* 3 (2), 77–101. https://doi.org/10.1191/1478088706qp063oa

[33] Akgun, S., Greenhow, C., 2022. Artificial intelligence in education: addressing ethical challenges in K-12 settings. *AI Ethics* 2, 431–440. https://doi.org/10.1007/s43681-021-00096-7

[34] Government of India, 2023. *The Digital Personal Data Protection Act, 2023 (Act No. 22 of 2023)*. Ministry of Law and Justice, New Delhi.

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