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Article

AI-Driven Public Finance Models for Scaling Inclusive Education in India: A Design-Science Framework for a Developing Economy

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Abstract: India has made substantial progress in expanding school access, yet the financing of inclusive education remains constrained by regional inequalities, uneven infrastructure, teacher deployment gaps, fragmented data systems, and weak links between public expenditure and learning outcomes. This article proposes an AI-driven public finance model for scaling inclusive education in India. Using a design-science and policy-analysis approach, the study synthesizes recent evidence from Indian education policy, UDISE+ school statistics, Samagra Shiksha, the National Education Policy 2020, and international research on AI in public financial management, education finance, and algorithmic governance. The proposed model integrates seven functions: education data integration, predictive budget forecasting, equity-weighted resource allocation, HR analytics for teacher deployment, real-time expenditure monitoring, outcome-based evaluation, and responsible AI governance. The framework is designed to support inclusive education for children with disabilities, girls, rural learners, socio-economically disadvantaged groups, and students in under-resourced districts. The article argues that AI should be treated not as a replacement for public decision-making but as a decision-support infrastructure that improves fiscal targeting, transparency, and accountability. The study contributes a context-specific conceptual model for India and offers policy recommendations for ministries, state governments, district education offices, and development partners seeking to align digital public infrastructure with SDG 4 and inclusive growth.

Keywords: artificial intelligence, public finance, inclusive education, India, education finance, HR analytics, UDISE+, Samagra Shiksha, responsible AI, SDG 4

1. Introduction

Inclusive education is no longer a peripheral welfare objective; it is a central requirement for equitable human-capital formation, social mobility, and sustainable development. In India, the challenge is particularly important because school education must serve a highly diverse population across caste, gender, disability, language, income, geography, migration status, and digital access. The National Education Policy 2020 places equity and inclusion at the centre of educational transformation and explicitly recognises socio-economically disadvantaged groups as a policy priority (Ministry of Education, 2020). However, the translation of policy commitments into outcomes depends on the quality of public finance. Inclusive education requires not only schools and teachers but also accessible infrastructure, assistive devices, special educators, transport, language-sensitive materials, digital connectivity, remedial support, and continuous monitoring.

India already has several policy instruments that can support inclusive education. Samagra Shiksha integrates school education from pre-school to Class XII and is aligned with SDG 4 and NEP 2020; it also includes interventions for children with special needs, such as identification and assessment, aids and appliances, assistive devices, teaching-learning materials, training of teachers, and stipends for girls with special needs (Department of School Education and Literacy, 2026; Samagra Shiksha, 2026). UDISE+ has created one of the world's largest school education management information systems, covering schools, enrolment, teachers, infrastructure, and other indicators (Ministry of Education, 2024). Yet these systems often remain underused for dynamic public financial management. Budgets are still frequently prepared on historical norms and administrative rules rather than predictive analytics, school-level need, and real-time evidence of exclusion.

The current fiscal challenge is not simply that more money is required, although sustained financing is clearly important. The deeper issue is that education finance must become more intelligent, equitable, and accountable. Public expenditure needs to reach the specific schools, learners, and districts where marginalisation is concentrated. The 2024 Education Finance Watch emphasises that education financing must be assessed through adequacy, efficiency, and equity, rather than aggregate spending alone (UNESCO Institute for Statistics, Global Education Monitoring Report Team, & World Bank, 2024). In India, the same logic applies to Union, state, district, and school-level education finance. A rupee spent on inclusive education has different social value depending on whether it reaches a school without ramps, a girl at risk of dropout, a child with disability requiring assistive technology, a teacher working in a single-teacher school, or a district with low transition rates.

Artificial intelligence offers a promising but sensitive pathway for improving this allocation problem. AI can analyse large, multi-source datasets, forecast enrolment and infrastructure needs, detect anomalies in expenditure flows, support teacher deployment, and evaluate whether funds are improving inclusion and learning. Recent OECD work on AI in public financial management highlights the potential of AI for forecasting, budget execution analysis, anomaly detection, and decision support, while also warning that public-sector AI requires transparency, accountability, and strong governance (OECD, 2025). For India, the opportunity is to combine existing digital public infrastructure, UDISE+, public expenditure data, and school-level planning with responsible AI systems that help government officials make better financing decisions.

This article therefore asks: How can AI-driven public finance models help India scale inclusive education in an equitable, accountable, and fiscally sustainable manner? The study develops a conceptual model using design-science reasoning and secondary evidence. It contributes to the literature in three ways. First, it connects AI, public finance, and inclusive education, which are often studied separately. Second, it provides an India-specific framework that uses existing policy architecture such as NEP 2020, Samagra Shiksha, UDISE+, DIKSHA, PM SHRI, and Digital India. Third, it proposes governance safeguards so that AI-enabled finance strengthens rather than weakens public accountability.

The research gap is important because most current discussions of artificial intelligence in education focus on teaching, learning analytics, personalised learning, assessment, or administrative automation. These are valuable areas, but they do not fully address the upstream question of how public money is allocated before educational services reach learners. Similarly, the public finance literature increasingly discusses AI for tax administration, audit, fraud detection, and budget forecasting, but less attention is paid to how these tools can be designed specifically for inclusive social-sector financing. This article fills that gap by treating education finance as an algorithmically supportable governance problem. The central claim is that inclusive education cannot be scaled only by adding technology to classrooms; it also requires smarter fiscal architecture that directs resources to learners and schools with the highest need.

The Indian case is particularly suitable for such a framework because it combines scale, diversity, and digital infrastructure. India has millions of teachers, hundreds of thousands of schools, multiple layers of public finance, and large inter-state variations in educational access and quality. It also has increasingly rich administrative data and policy interest in AI for social development. This combination creates both an opportunity and a responsibility. The opportunity is to use data for better planning and accountability. The responsibility is to ensure that the use of AI does not intensify exclusion, stigmatise vulnerable learners, or shift public decision-making into opaque technological systems.

2. Methods

This study uses a design-science research approach combined with policy document analysis and integrative literature synthesis. Design science is appropriate because the objective is not to test a single hypothesis with primary survey data but to develop a policy-relevant artefact: an AI-driven public finance model for inclusive education. The artefact is evaluated conceptually by examining whether it addresses a clearly defined policy problem, draws from reliable evidence, aligns with institutional realities, and produces actionable outputs for public decision-makers.

The study reviewed three categories of secondary material. The first category consisted of Indian policy and administrative sources, including the National Education Policy 2020, Samagra Shiksha documentation, UDISE+ publications, NITI Aayog's National Strategy for Artificial Intelligence, and education budget announcements. These sources establish the Indian policy context and define the administrative feasibility of the model. The second category included international policy reports from UNESCO, UNICEF, the World Bank, and OECD on education finance, digital education, AI governance, learning poverty, and public financial management. These sources provide global standards for equity, financing, and responsible AI. The third category included peer-reviewed research on AI in public-sector accountability, algorithmic fairness, AI in education, learning analytics, and public administration. This literature was used to identify risks and design principles.

The analytical procedure followed four steps. First, the financing problem was decomposed into core functions: forecasting, allocation, execution, monitoring, evaluation, and governance. Second, AI applications were mapped to each function. For example, predictive models were linked to enrolment forecasting; anomaly detection was linked to expenditure monitoring; optimisation models were linked to resource allocation; and explainable AI was linked to governance. Third, inclusion variables were identified from Indian policy priorities and SDG 4 commitments, including gender, disability, rurality, socio-economic disadvantage, teacher availability, digital access, infrastructure, and learning outcomes. Fourth, these elements were combined into a layered model that can be implemented at national, state, district, and school levels.

The study is conceptual and does not claim to estimate causal effects. Instead, it proposes a framework that can be empirically tested in future research using district-level UDISE+ data, state budget data, Samagra Shiksha plans, school grants, teacher records, and learning assessment results. This limitation is deliberate because the immediate research need is to define an implementable model before conducting pilots. A premature empirical model without a governance design could increase the risk of biased or opaque decision-making. Therefore, the methodology places equal emphasis on technical feasibility and public accountability.

The proposed model is evaluated against five criteria: relevance to India's inclusive education goals; compatibility with existing data and finance systems; capacity to improve equity in resource allocation; ability to support accountability in expenditure; and alignment with responsible AI principles such as fairness, transparency, privacy, human oversight, and contestability. These criteria are derived from the OECD's work on AI in government, UNICEF's child-centred AI principles, and the algorithmic fairness literature (Aldemir & Uysal, 2025; Kizilcec & Lee, 2020; OECD, 2025; UNICEF, 2026b).

3. Results

The main result of the study is the AI-Enabled Inclusive Education Public Finance Model for India. The model is not a single software application. It is a governance and analytics architecture that links education data, public finance, AI decision support, and inclusive education outcomes. It has seven connected components: data integration, predictive budget forecasting, equity-weighted allocation, HR analytics, expenditure monitoring, outcome evaluation, and responsible AI governance.

The first component is education data integration. India has a strong foundation through UDISE+, DIKSHA, state education portals, scholarship databases, teacher information systems, school infrastructure records, and public finance systems. However, these systems often operate in silos. An AI-driven finance model requires a secure data layer that links school identifiers, district identifiers, budget heads, physical infrastructure, teacher availability, enrolment, attendance, disability indicators, gender indicators, learning outcomes, and grant utilisation. The goal is not to centralise all personal data in a risky manner but to build interoperable, role-based, and privacy-preserving data pipelines. UNICEF's digital education strategy stresses that digital transformation must move beyond isolated platforms and strengthen systems through evidence-based and human-centred design (UNICEF, 2026a).

The second component is predictive budget forecasting. Traditional budgeting often uses previous-year expenditure plus incremental changes. This approach can miss rapid demographic shifts, migration, school consolidation effects, disability identification, and regional infrastructure needs. AI models can use historical enrolment, population projections, dropout patterns, transition rates, teacher vacancies, inflation, transport distances, and accessibility gaps to estimate future resource requirements. For example, a district with rising secondary enrolment but inadequate accessible classrooms would receive an early warning for capital expenditure. A block with high transition losses among girls could trigger transport, hostel, menstrual hygiene, safety, or scholarship interventions. Forecasting does not determine the budget by itself; it gives finance and education officials a better evidence base.

The third component is equity-weighted resource allocation. A simple per-student grant is insufficient because students have unequal needs. The model therefore proposes an inclusion-weighted allocation formula. The base amount per learner is adjusted using weights for disability, gender vulnerability, rural or remote location, socio-economic disadvantage, minority or tribal status where relevant, school infrastructure deficit, teacher shortage, language need, and digital exclusion. The formula should be transparent and publicly explainable. It can be expressed as: Inclusive Education Allocation = Base Grant + Student Need Weight + School Infrastructure Weight + Teacher Support Weight + Digital Access Weight + District Vulnerability Weight. This structure allows funds to follow need rather than only enrolment size.

The fourth component is HR analytics for teacher deployment. Inclusive education cannot succeed without teachers, special educators, counsellors, resource persons, and trained school leaders. India faces uneven teacher deployment, single-teacher schools in several regions, and subject-specific shortages. HR analytics can identify teacher gaps, forecast retirements, monitor pupil-teacher ratios, recommend rational deployment, and prioritise professional development. Importantly, the model should not use HR analytics for punitive surveillance. Its purpose should be workforce planning, training support, and equitable staffing. Teacher data must be interpreted with contextual information, especially in remote and high-poverty areas where working conditions are difficult.

The fifth component is real-time expenditure monitoring. Education funds pass through multiple administrative layers before reaching schools and students. Delays, under-utilisation, misclassification, and procurement inefficiencies can weaken outcomes even when budgets are approved. AI-based anomaly detection can flag unusual spending patterns, repeated delays, sudden expenditure spikes near year-end, mismatch between sanctioned and utilised funds, or procurement patterns that require audit. The purpose is not to replace auditors but to prioritise human audit attention. OECD (2025) notes that AI can support public financial management by improving analysis of budget execution and identifying risks, but such systems must be governed carefully to avoid opaque decisions.

The sixth component is outcome-based evaluation. Inclusive education finance should be judged not only by spending completion but also by whether spending improves access, retention, participation, learning, safety, and dignity. The model therefore links expenditure to output and outcome indicators. Outputs may include ramps constructed, assistive devices delivered, teachers trained, digital devices shared, special educators appointed, and remedial sessions conducted. Outcomes may include improved attendance, reduced dropout, higher transition rates, increased participation of children with disabilities, improved foundational literacy and numeracy, and reduced gender or district gaps. UNICEF's strategy emphasises a shift from outputs to outcomes, asking whether children actually learned rather than merely whether they participated in a programme (UNICEF, 2026a).

The seventh component is responsible AI governance. The model requires safeguards because education data involve children and vulnerable groups. Governance mechanisms should include data minimisation, privacy-by-design, role-based access, algorithmic impact assessments, independent audits, fairness testing across groups, explainable model outputs, grievance redressal, and human-in-the-loop approval. UNICEF's AI strategy highlights child-centred principles such as necessity, non-discrimination, data protection, human oversight, transparency, explainability, accountability, and inclusion (UNICEF, 2026b). These principles are directly relevant to India's education finance context.

4. Discussion

The proposed model addresses a key weakness in existing education finance systems: the separation between planning, budgeting, implementation, and outcome evaluation. In many administrative settings, school data are collected for reporting, budget data are prepared for compliance, and learning outcomes are assessed through separate mechanisms. AI-driven public finance creates value only when these data streams are connected to decision-making. The model therefore treats AI as a public-sector decision-support system rather than a commercial education technology product.

For India, the model has strong institutional relevance because it builds on existing policy platforms. NEP 2020 already emphasises equity, inclusion, digital learning, teacher development, and governance reform (Ministry of Education, 2020). Samagra Shiksha already provides a national financing architecture for school education and includes inclusive education interventions for children with special needs. UDISE+ already provides school-level data. Digital India and the national AI strategy already identify AI as a tool for inclusive development (NITI Aayog, 2018). The proposed model does not require India to create an entirely new education system; it requires better integration, analytics, and accountability within existing systems.

A major advantage of AI-driven forecasting is that it can make invisible needs visible before they become crises. For instance, a school may appear adequately funded on paper but still fail inclusion if it lacks ramps, accessible toilets, assistive devices, subject teachers, or internet connectivity. A district may have acceptable aggregate enrolment while hiding high dropout among girls or children with disabilities. A state may report budget utilisation while under-spending on the most inclusion-sensitive components. AI can identify such patterns by combining administrative and financial data. This makes budgeting more anticipatory rather than reactive.

However, AI also creates risks. Algorithmic systems trained on historical data may reproduce historical injustice. If past data under-identify children with disabilities, the model may under-allocate resources to them. If dropout data are incomplete, the model may misread exclusion as absence of demand. If school-level reporting is manipulated, AI may amplify errors. Research on algorithmic fairness shows that fairness is not a purely technical property; it depends on measurement choices, institutional context, and the consequences of decisions (Barocas et al., 2023; Kizilcec & Lee, 2020; Pfeiffer et al., 2023). Therefore, the model must include fairness audits and human review.

The public finance dimension also requires caution. Efficiency should not be interpreted narrowly as cost-cutting. In inclusive education, efficient finance means spending where the social return and equity need are highest. A child with disability may require more resources than a child without disability; a remote school may require higher per-student expenditure than an urban school; a first-generation learner may require additional remedial support. Equity-weighted finance therefore accepts differentiated spending as a condition of fairness. This aligns with the SDG 4 commitment to inclusive and equitable quality education, which cannot be achieved through equal nominal spending alone.

The model also has implications for HR analytics. Teacher deployment is one of the most politically sensitive and operationally important areas in education finance. AI can support rational staffing by identifying gaps and projecting needs, but final decisions must consider teacher preferences, local languages, safety, transport, housing, and social context. A purely algorithmic transfer system would risk being unfair and could weaken morale. Therefore, the model recommends decision support rather than automated decision-making. Teachers should also be part of the design process because digital education strategies are more effective when teachers are treated as central agents rather than passive users (UNICEF, 2026a).

In terms of implementation, a phased strategy is preferable. The first phase should develop a data-readiness and governance audit across selected states. The second phase should pilot district-level dashboards for forecasting and equity-weighted allocation. The third phase should integrate expenditure monitoring with Samagra Shiksha financial flows. The fourth phase should evaluate outcomes using learning, inclusion, and retention indicators. The fifth phase should scale only after independent audits demonstrate fairness, usefulness, and administrative feasibility. This staged approach reduces the risk of technology-led reform without institutional capacity.

The article also contributes to research. Existing literature has examined AI in education, AI ethics, and public financial management, but the intersection of AI-driven public finance and inclusive education remains underdeveloped. By proposing a model for India, the study shows how AI can be embedded in public budgeting rather than limited to classroom learning applications. This is especially important because many education technology debates focus on devices, content, and adaptive learning, while the financing system that determines who receives resources remains less digitised and less intelligent.

For policymakers, the model suggests several practical actions. Ministries should establish interoperable data standards linking UDISE+, finance, HR, and outcome systems. State governments should create equity-weighted grant formulas that are explainable and auditable. District education offices should use predictive dashboards for planning, not only for compliance reporting. Finance departments should adopt AI-assisted risk flags for expenditure monitoring. Independent bodies should conduct algorithmic impact assessments. School management committees and civil society should have access to simplified public dashboards that show whether inclusive education funds are reaching intended beneficiaries.

The model also requires legal and ethical safeguards. Children's data must not be used for profiling or exclusion. Sensitive attributes such as disability, caste, income, gender, and location should be used only to improve resource allocation and reduce inequality, not to label learners negatively. Data governance should follow principles of necessity, proportionality, minimisation, accountability, and contestability. Any family, school, or district affected by an AI-supported allocation decision should have a mechanism to question or correct data. Public trust will depend on the ability to explain why a district or school received a particular allocation.

There are limitations to this study. It is a conceptual paper and does not empirically estimate the budgetary gains of AI adoption. It also does not provide a software prototype. Future studies should test the model using district-level data from selected Indian states, compare AI-supported allocation with existing allocation patterns, and examine whether equity-weighted finance improves outcomes for marginalised learners. Researchers should also evaluate cost-effectiveness, administrative burden, and user acceptance among education officials and teachers.

The theoretical implication of the article is that public finance for inclusive education should be understood as a socio-technical system. Fiscal rules, data standards, algorithms, institutional accountability, and local educational realities interact with one another. A technically accurate model may fail if it does not fit administrative routines; a politically acceptable model may fail if it does not correct inequity; and a well-funded programme may fail if spending cannot be linked to outcomes. The proposed framework therefore integrates three logics: the equity logic of inclusive education, the efficiency logic of public financial management, and the accountability logic of responsible AI governance.

The managerial implication is that education administrators need new capacities. Future education finance teams will require not only accountants and programme officers but also data stewards, AI-literate planners, monitoring specialists, and inclusion experts. This does not mean every district must employ advanced data scientists. It means that public officials should understand what AI models can and cannot do, how to interpret risk scores, how to question biased outputs, and how to document final decisions. Capacity building is therefore as important as software development. Without trained users and clear institutional ownership, AI dashboards may become another reporting layer rather than a tool for reform.

The social implication is that AI-enabled public finance can help make inclusion more concrete. Inclusive education is sometimes discussed in broad moral language, but public budgets require operational categories, unit costs, timelines, and accountability indicators. An AI-supported finance model can translate inclusion into measurable planning questions: Which schools lack accessible infrastructure? Which children require assistive devices? Which districts need more special educators? Which budget lines are delayed? Which interventions improve retention? When these questions are answered transparently, public finance becomes a mechanism for social justice rather than only an accounting exercise.

5. Policy Implementation Roadmap for India

A practical implementation roadmap should begin with governance rather than technology procurement. The Government of India and state governments should first define the public purpose of AI-enabled education finance: to improve inclusion, equity, transparency, and learning outcomes. Once the purpose is defined, data-sharing protocols, accountability rules, and grievance mechanisms can be designed. Only then should AI tools be procured or developed. This sequence is important because technology purchased without governance often creates vendor dependence and weak public accountability. Procurement should therefore require open standards, model documentation, audit access, data portability, cybersecurity safeguards, and clear exit clauses so that public agencies remain in control of educational data and financial decisions.

At the national level, the Ministry of Education can develop a reference architecture for AI-enabled education finance. This architecture should define data standards, model documentation requirements, privacy safeguards, and minimum fairness tests. It should also identify which decisions may be automated and which must remain human-approved. High-stakes decisions such as school closure, teacher transfer, denial of funds, or learner eligibility should never be fully automated. AI may provide recommendations, but public officials should record reasons for accepting or rejecting them.

At the state level, governments can adapt the model to local priorities. For example, tribal areas may assign greater weight to language, transport, and residential schooling; urban areas may focus on overcrowding, migrant children, and digital access; flood-prone or conflict-affected districts may require resilience indicators. This flexibility is necessary because India is administratively and socially diverse. A national model should provide principles, not impose a single formula that ignores state-level realities.

At the district level, the model can support school development planning. District officials can use dashboards to identify schools with high inclusion gaps, under-utilised grants, teacher shortages, or infrastructure deficits. They can also simulate how different budget scenarios would affect access, retention, and learning. A district-level officer should be able to ask: Which schools need immediate accessibility investment? Where are girls most at risk of dropping out? Which schools need special educators? Which budget heads are consistently delayed? Which interventions produce measurable improvement? AI can help answer these questions, but officials must retain responsibility for final action.

At the school level, the system should reduce reporting burden rather than increase it. Many teachers already face heavy administrative workloads. Data collection should therefore be integrated into existing systems and simplified through mobile or web-based tools. Schools should receive feedback from the data they submit. If teachers and head teachers only send data upward without receiving useful planning insights, the system will not build trust. The model must therefore provide school-level benefits such as need assessment, grant planning, teacher training recommendations, and inclusion checklists.

The roadmap should also include community-facing transparency. School management committees, parents, local bodies, and civil society organisations should be able to access simplified information on inclusive education grants, infrastructure gaps, and progress indicators. Public dashboards need not reveal personal data; they can report aggregated school or district indicators. Such transparency can strengthen social audit, reduce misinformation, and ensure that AI-enabled planning remains connected to local democratic accountability. In a federal system like India, this balance between national standards and local participation is essential for legitimacy.

6. Conclusion

This article proposed an AI-driven public finance model for scaling inclusive education in India. The model responds to a real policy challenge: India has broad education commitments and significant digital systems, but inclusive education financing still requires more precise forecasting, equitable allocation, expenditure monitoring, HR planning, and outcome evaluation. AI can help address these gaps if it is embedded within responsible public governance.

The proposed model integrates education data, predictive analytics, equity-weighted budgeting, HR analytics, expenditure monitoring, outcome evaluation, and responsible AI safeguards. It is designed to support children with disabilities, girls, rural learners, socio-economically disadvantaged groups, and students in under-resourced districts. It also aligns with NEP 2020, Samagra Shiksha, UDISE+, SDG 4, and India's broader AI-for-social-good agenda.

The central argument is that inclusive education finance must move from historical budgeting to intelligent, equity-sensitive, evidence-based public financial management. However, AI should not replace democratic decision-making. It should function as a transparent decision-support infrastructure that improves the quality of public reasoning. The success of AI-driven finance will depend less on algorithmic sophistication alone and more on data quality, institutional capacity, human oversight, fairness testing, and public accountability.

For India, the opportunity is significant. A carefully governed AI-enabled finance model can help ensure that funds reach the schools and learners with the greatest need. It can reduce leakage, improve teacher deployment, identify infrastructure gaps, and link expenditure to inclusion outcomes. Future empirical research should test the model in selected districts and measure its effects on equity, efficiency, and learning. If implemented responsibly, AI-driven public finance can become a powerful instrument for making inclusive education not only a policy promise but an operational reality.

Table 1: Key Variables for an AI-Driven Inclusive Education Finance Model

Variable group	Illustrative indicators	AI function	Public finance use
Learner inclusion	Gender, disability, socio-economic disadvantage, rurality, language, caste/tribe where legally and ethically appropriate	Risk mapping and equity scoring	Need-based grants and targeted support
School infrastructure	Ramps, accessible toilets, classrooms, electricity, internet, libraries, assistive technology	Gap detection and capital planning	Prioritisation of infrastructure expenditure
Teacher and HR data	Teacher availability, vacancies, special educators, subject gaps, training needs	HR forecasting and deployment analytics	Teacher recruitment, transfer support, and professional development
Finance and expenditure	Budget allocation, releases, utilisation, procurement, delays, school grants	Anomaly detection and execution monitoring	Audit prioritisation and reduction of leakage
Outcomes	Attendance, retention, transition, foundational learning, CWSN participation, gender parity	Impact evaluation and scenario analysis	Outcome-informed budget revision

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Conceptual Architecture of the Proposed Model

1. Data integration layer: UDISE+, finance, HR, school infrastructure, learning outcomes

2. Predictive analytics layer: demand forecasting, risk mapping, dropout and infrastructure prediction

3. Equity-weighted allocation layer: base grant plus need, infrastructure, teacher, digital, and district vulnerability weights

4. HR analytics layer: teacher deployment, special educator planning, training and workload support

5. Expenditure monitoring layer: release tracking, utilisation analysis, anomaly detection and audit flags

6. Outcome evaluation layer: access, retention, inclusion, learning, safety and SDG 4 indicators

7. Responsible AI governance layer: privacy, explainability, fairness audit, human oversight and grievance redressal

Figure 1: Conceptual Architecture of the Proposed Model