

Original Article**Artificial Intelligence for Institutional Accreditation in India: A Framework for NAAC's Data-Driven Quality Assurance****Ajinkya S. Kumbhar**

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**Abstract**

For nearly three decades, the National Assessment and Accreditation Council (NAAC) has been India's main mechanism for assuring quality in higher education. Its traditional model — built around a self-reported Self-Study Report, a data validation stage, and an on-site peer-team visit ending in a letter grade — has come under increasing strain. Critics point to slow turnaround, difficulty in standardizing judgments across assessor teams, and the challenge of scaling the process to the thousands of institutions India now wishes to bring under formal quality review.

In February 2025, NAAC announced a major reform: a binary accreditation outcome, an optional five-level Maturity-Based Graded Level (MBGL) scale for institutions seeking continuous improvement, a unified national data platform, and the beginnings of an AI-assisted evaluation engine to reduce the burden of manual verification. This paper builds on that reform and proposes, in concrete technical terms, what such an AI-assisted engine could look like. We outline a system that can read and structure Self-Study Reports, cross-check institutional claims against government data sources such as UGC, AICTE, AISHE and NIRF, benchmark institutions against their peers, and present the results to human assessors without replacing their judgment. The discussion is grounded in India's higher-education context: wide variation in digital readiness across institutions, obligations under the Digital Personal Data Protection Act, 2023, and the well-known risk that metric-driven systems can encourage institutions to "write to the metric" rather than improve underlying quality. We conclude with a phased pilot study to test the framework before any wider rollout.

Keywords: accreditation, NAAC, artificial intelligence, machine learning, natural language processing, higher education, quality assurance, India

Introduction

Quality assurance in Indian higher education is largely channelled through the National Assessment and Accreditation Council (NAAC), an autonomous body established under the University Grants Commission in 1994. NAAC's mandate is to assess universities and colleges against a common set of quality benchmarks. With the National Education Policy (NEP) 2020 positioning accreditation as a central lever for accountability, NAAC's task has become significantly more demanding. It is now expected to evaluate thousands of institutions that vary widely in size, resources, location and digital maturity.

The legacy process was not designed for this scale. Institutions prepared a narrative Self-Study Report organised around seven quality criteria. Verifying these claims without a physical visit was difficult. On-site visits, in turn, were costly, slow to schedule, and dependent on the judgment of small assessor teams, leading to inconsistencies across institutions. Over time, a familiar set of concerns emerged: accreditation cycles were long, coverage of eligible institutions remained uneven, and outcomes sometimes appeared to depend as much on the assigned assessors as on the institution's actual quality. NAAC's 2025 reform, announced on 10 February following the recommendations of a committee chaired by former ISRO chairman Dr K. Radhakrishnan, seeks to address these issues by shifting from narrative to data. The earlier CGPA-style letter grades are being replaced by a binary accreditation outcome, with an optional five-level MBGL scale for institutions that wish to demonstrate continuous improvement. A unified national data platform is intended to verify institutional claims against records already held by UGC, AICTE, AISHE and NIRF, supported by an AI-assisted evaluation engine to automate much of the verification work that previously required physical visits. This paper takes NAAC's stated direction as its starting point and translates it into a concrete, buildable framework. We propose a modular AI system aligned with NAAC's existing IIQA-SSR-DVV workflow, designed to support — not supplant — human peer review.

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Section 2 describes NAAC's process and the 2025 reforms. Section 3 reviews relevant work in the Indian and accreditation literature. Section 4 presents the proposed framework. Section 5 outlines a methodology for empirical validation. Section 6 discusses benefits, limitations and ethical considerations, and Section 7 concludes.

NAAC's Accreditation Process and the 2025 Reforms

The Process as It Stood

Under the earlier system, an institution seeking accreditation submitted an Institutional Information for Quality Assessment (IIQA), prepared a detailed Self-Study Report (SSR) across seven quality criteria, underwent a Data Validation and Verification (DVV) stage, and hosted an on-site peer visit. The outcome was a letter grade ranging from A++ to C or D. Re-accreditation was due in the fourth year of a five-year cycle, ensuring regular review for all accredited institutions.

Binary Accreditation and MBGL

The 2025 reform replaces the letter-grade scale with a binary outcome: an institution is either accredited or not. Institutions that meet this threshold may optionally pursue a Maturity-Based Graded Level (MBGL) rating on a five-level scale, recognising sustained improvement beyond the basic pass mark. Lower MBGL levels are assessed primarily through digital submissions, while higher levels involve hybrid review and direct expert interaction. Institutions holding grades under the older Revised Accreditation Framework may retain them for the remainder of their five-year term during the transition. The new framework also allows foreign universities with campuses in India to apply for accreditation.

Where AI Is Meant to Fit In

NAAC's reform documents assign AI a specific role: benchmarking an institution's submitted data against peer groups and national averages, and cross-checking that data against records held by UGC, AICTE, AISHE and NIRF through the proposed One Nation One Data Platform. The aim is to catch inconsistencies automatically rather than relying on manual spot-checks during site visits. As of mid-2025, this AI engine remained in a pilot stage, and the supporting digital portal had not yet gone live on the originally announced timeline. This gap between policy intent and implemented system motivates the present work: NAAC has articulated what it wants AI to do, but not yet how such a system should be architected in detail.

Related Work

A growing body of literature explores the use of AI in accreditation-style quality assurance. In the Indian context, discussions around NEP 2020, NAAC reforms and the One Nation One Data Platform emphasise principles that align with global best practice: human control over decisions, verifiable data, transparency, accountability, security and system reliability wherever AI supports accreditation.

Where NLP-based review of self-study documents has been piloted, reported gains are significant. Tasks such as skimming long appendices or consolidating statistics from scattered sections — which once took reviewers many hours — have been reduced to minutes, always framed as augmenting rather than replacing human judgment. Technical proposals have demonstrated that machine-learning pipelines for accreditation-style scoring are feasible: for example, studies using k-means clustering and template-matching to classify institutions against quality criteria suggest that the building blocks for NAAC's proposed AI engine already exist in the research literature, even if not yet deployed at national scale in India.

Two insights from this literature are particularly relevant. First, the most deployable AI applications today focus on document understanding and cross-source data verification — structuring self-reported claims and checking them against other records — rather than automated judgment of qualitative institutional quality. Second, serious guidance consistently treats AI as supporting, not replacing, human reviewers. NAAC's 2025 announcement aligns with this spirit, but existing writing on the reform remains at the policy level rather than offering system design. This paper addresses that gap by translating NAAC's goals into an architecture that can be built around its existing SSR and DVV workflow.

Proposed AI Framework for NAAC Accreditation

The proposed framework consists of four modules, summarised in Table 1. It is designed to integrate with NAAC's existing IIQA–SSR–DVV workflow, not replace it. Consistent with the literature, AI handles repetitive, high-volume checking tasks that consume most of the assessment timeline, while the final accreditation decision — especially regarding qualitative aspects — remains with the human peer-review team.

Table 1. Proposed AI modules mapped to NAAC's assessment workflow

Module	Core Function	Representative AI/ML Techniques
SSR Document Understanding	Parses narrative Self-Study Reports and Data Capture Formats to extract structured, criterion-wise claims (faculty strength, publications, infrastructure, student support) for downstream checking.	Transformer-based NLP, named-entity extraction, table/figure parsing from PDF submissions
Cross-Source Verification	Compares extracted SSR claims against independent records held in UGC, AICTE, AISHE and NIRF databases and flags discrepancies for assessor attention.	Record-linkage algorithms, rule-based consistency checks, statistical outlier/anomaly detection
Peer-Benchmarking and MBGL Scoring	Positions an institution's verified metrics against peer-group and national distributions to support binary accreditation and MBGL classification.	Clustering (e.g., k-means), weighted scoring/template-matching models, regression-based benchmarking
Assessor Decision-Support Dashboard	Presents verified data, flagged discrepancies and benchmark scores to human peer-review teams, preserving final judgment with assessors rather than the algorithm.	Interactive visual analytics, explainable-AI summaries of flagged items

SSR Document Understanding

Institutions submit Self-Study Reports and supporting Data Capture Formats as lengthy narrative and tabular documents. An NLP module can read these submissions and extract structured, criterion-wise claims: faculty numbers and qualifications, publication counts, infrastructure details, student-support indicators. This transforms free-text and tabular evidence into a form that can be compared against other data sources, reducing the manual effort required to review long documents.

Cross-Source Verification

Once claims are extracted, a verification module checks them against independent records held by UGC, AICTE, AISHE and NIRF — the same cross-referencing role assigned to the proposed One Nation One Data Platform in NAAC's reform documents.

The module flags discrepancies for human review rather than making decisions autonomously. This preserves human control while giving assessors a stronger basis for catching inconsistencies that manual spot-checks might miss.

Peer-Benchmarking and MBGL Scoring

A benchmarking module positions an institution's verified metrics relative to peer-group and national distributions. Using clustering or weighted-scoring methods demonstrated in prior AI-based quality-assurance research, this module supports both the binary accreditation decision and, for institutions pursuing it, placement on the appropriate MBGL level. This provides institutions with earlier, clearer feedback on their standing than a single grade delivered at the end of the cycle.

Assessor Decision-Support Dashboard

Outputs from the three modules are integrated into a dashboard for IQAC coordinators and NAAC peer-review teams. The dashboard displays verified data, explains why each discrepancy was flagged, and shows where the institution stands relative to its benchmark group. The design ensures that the accreditation decision remains human, informed by AI findings rather than delegated to them.

Proposed Methodology for Empirical Validation

The framework above is a conceptual design. Empirical validation would proceed in phases:

- **Phase 1 — Requirements elicitation:** Engage IQAC coordinators and NAAC peer-review team members across diverse institutions — universities, autonomous colleges, affiliated colleges, across multiple states — to validate the data fields and workflow assumptions in Section 4.
- **Phase 2 — Prototype development:** Build a limited prototype covering document understanding and cross-source verification for one or two NAAC criteria. Test against a sandboxed set of AICTE/AISHE-style reference data.
- **Phase 3 — Pilot deployment:** Conduct a voluntary pilot with a small number of institutions preparing an SSR. Compare verification time and discrepancy detection rates against the manual DVV process.
- **Phase 4 — Evaluation:** Quantitatively compare turnaround time and discrepancy-detection rates. Gather qualitative feedback from IQAC coordinators and assessors on trust, usability and perceived value of the system's outputs.

Discussion

Benefits

If implemented as intended, the framework should deliver on NAAC's reform objectives: reduced time spent on manual document review, more consistent flagging of data discrepancies across assessors, earlier and more specific feedback to institutions through MBGL benchmarking, and a process capable of scaling to the tens of thousands of institutions under NAAC's purview.

Limitations and Implementation Challenges

Significant challenges remain. A digital divide exists between well-resourced institutions and smaller, often rural colleges that may lack digitised records or technical staff to integrate with an API-driven verification pipeline. If unaddressed, this could skew accreditation outcomes in favour of already-advantaged institutions. India's Digital Personal Data Protection Act, 2023 imposes limits on processing personal data — such as faculty records or student data used as evidence — in a centralised system, with direct implications for system architecture. Finally, any metric-driven system risks encouraging institutions to optimise for measured indicators rather than underlying quality. This is why the framework keeps AI outputs advisory, preserving human judgment over final decisions.

Ethical Considerations

Automated flagging will produce false positives. A flagged discrepancy could unfairly delay or harm an institution's accreditation outcome, particularly for less-resourced institutions where weaker data infrastructure reflects capacity constraints rather than poor quality. Any deployment must include a timely, transparent mechanism for institutions to contest flagged findings, in line with accountability principles emphasised in Indian policy discussions and UNESCO's ethics guidance on AI in education. Benchmarking also raises important questions about peer-group definition: if not carefully designed, comparison groups could structurally disadvantage newer or resource-constrained institutions against long-established ones.

Conclusion

NAAC's 2025 reforms mark a serious effort to shift institutional quality assurance in India toward a more data-driven, consistent and scalable model. This paper has proposed a concrete technical framework to support that vision: a modular AI system for SSR document understanding, cross-source verification, peer-benchmarking and decision support, designed to keep final accreditation judgments in human hands. Successful national-scale implementation will require attention to disparities in digital readiness, compliance with India's data-protection law, safeguards against gaming of metrics, and transparent processes for institutions to contest automated findings. The next step is a phased pilot, as outlined in Section 5, to test the framework with real institutions and data before considering wider rollout as part of NAAC's binary accreditation and MBGL framework.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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