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A Multi-Criteria Mathematical Model for Evaluating NAAC Accreditation Readiness of Arts and Science Colleges

Dr. M. Vijayakumar[1], Dr. K. R. Ananth[2], Dr. T. Annadurai[3], Dr. V. C. Srinivasan[4]
[1]Associate Professor / HEAD, Departmment of Computer Technology, Nandha Arts and Science College(AUTONOMUS), Erode.
Orcid Id : https://orcid.org/0000-0001-7386-4836
vij370@gmail.com
[2]Professor/ Head, Department of Artificial Intelligence, Nandha Arts and Science College, Erode
Mail ID: sapujaa@gmail.com
[3]Associate Professor, Department of Tamil, Nandha Arts and Science College (Autonomous), Erode
annadurai.t@nandhaarts.org
Orcid id : http://www.orcid.org/0009-0002-4132-0855
[4]Administrative Officer, Nandha Arts and Science College (Autonomous), Erode.
srivc2345@gmail.com
[5]Orcid Id: https://orcid.org/0009-0008-9926-7982

Abstract: The National Assessment and Accreditation Council (NAAC) evaluates Indian higher education institutions on seven weighted criteria that span curricular design, teaching quality, research output, infrastructure, student support, governance, and institutional values. For arts and science colleges, especially those functioning with constrained budgets and largely undergraduate teaching mandates, gauging readiness for this assessment before formally engaging with it is often done informally, through checklists and committee impressions rather than a structured quantitative process. This paper develops a multi-criteria mathematical model that converts NAAC's seven-criteria structure into a composite, numerically defensible Accreditation Readiness Index. The model combines the Analytic Hierarchy Process (AHP) for deriving criterion weights from expert pair wise judgments with a Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranking procedure, and it incorporates a triangular fuzzy extension to absorb the subjectivity inherent in indicators such as governance quality or institutional values that resist crisp numerical description. A worked illustration involving five hypothetical arts and science colleges demonstrates how the model separates institutions that are genuinely accreditation-ready from those that merely appear so on isolated metrics. A sensitivity analysis further shows how the ranking of colleges shifts when criterion weights are perturbed, offering administrators a way to identify which improvement levers yield the largest gain in readiness per unit of institutional effort. The paper closes by discussing the practical value of the model for internal quality assurance cells, its current limitations, and directions for extending it with machine-learning-assisted weight elicitation.
Keywords: NAAC accreditation; accreditation readiness; multi-criteria decision making; Analytic Hierarchy Process; TOPSIS; fuzzy evaluation; arts and science colleges; higher education quality assurance.

I. INTRODUCTION

Quality assurance has become one of the defining preoccupations of Indian higher education over the past two decades. The National Assessment and Accreditation Council, set up under the aegis of the University Grants Commission, has positioned itself as the principal external mechanism through which colleges and universities demonstrate that their teaching, research, and governance meet a nationally recognised standard (National Assessment and Accreditation Council, n.d.). For arts and science colleges, many of which operate as affiliated units of a larger university with comparatively modest research budgets, the accreditation process is simultaneously an opportunity and a source of considerable anxiety. It is an opportunity because a favourable grade widens access to government grants, autonomy status, and public trust; it is a source of anxiety because the assessment instrument itself is dense, spans seven weighted criteria, and increasingly leans on data-verified, outcome-based metrics rather than descriptive narrative (OpenEducat, 2026).

A recurring difficulty for internal quality assurance cells (IQACs) is that readiness for accreditation is rarely a single number. A college may possess excellent physical infrastructure while lagging in research output; another may have a vibrant curriculum but weak governance documentation. Committees therefore tend to rely on informal, criterion-by-criterion impressions when deciding whether to apply for assessment in a given cycle, and this informality can lead to both premature applications, which risk an unfavourable grade, and unnecessary delay, where a college that is in fact ready postpones the process out of excess caution. What is missing, in most institutional settings, is a structured way of aggregating heterogeneous, partly qualitative and partly quantitative indicators into a single readiness signal that can be tracked over time and compared across departments.

Multi-criteria decision making (MCDM) offers exactly this kind of aggregation logic, and it has already been applied productively to several adjacent problems in higher education, including university accreditation workflows (Benmoussa et al., 2019), NAAC grade prediction for engineering institutions (Dey Mondal et al., 2024), lecturer performance evaluation (Do et al., 2024), student selection (James et al., 2023), and university performance benchmarking more generally (Wang et al., 2022). What remains comparatively underexplored in the literature is a readiness model built specifically around the seven NAAC criteria and calibrated to the particular constraints of arts and science colleges, where research infrastructure and doctoral supervision capacity are typically thinner than in university departments or professional institutes.

This paper attempts to close that gap. It proposes a mathematical model that (a) operationalises the seven NAAC criteria and their constituent key indicators as a formal decision matrix, (b) derives objective and expert-informed weights for these criteria using the Analytic Hierarchy Process, (c) aggregates the weighted, normalised indicator scores into a single Composite Readiness Index using a TOPSIS-based procedure, and (d) accommodates the linguistic vagueness of qualitative indicators through a triangular fuzzy number extension. The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on MCDM applications in higher education quality assessment. Section 3 states the research problem and objectives. Section 4 summarises the NAAC assessment framework. Section 5 presents the proposed mathematical model in full. Section 6 illustrates the model on a hypothetical dataset of five colleges. Section 7 discusses the results, Section 8 reports a sensitivity analysis, Section 9 draws out practical implications, Section 10 notes limitations, and Section 11 concludes.

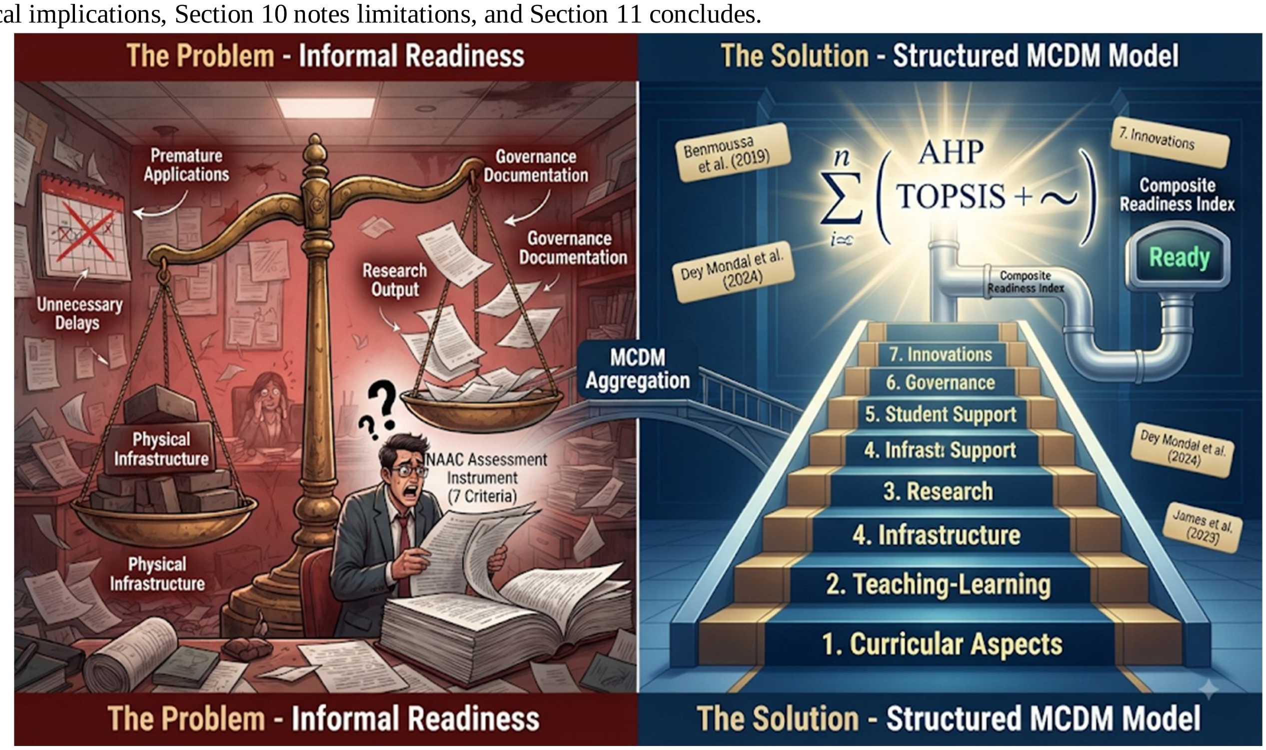

Fig 1: From Chaos to Clarity: Transitioning from Informal Assessment Readiness to a Structured MCDM Model

This split conceptual illustration contrasts a chaotic, stressed academic office struggling with disorganized NAAC accreditation readiness (left) with a streamlined, structured mathematical framework using Multi-Criteria Decision-Making models (right). A central bridge links the messy manual evaluation process to an efficient, transparent digital readiness index.

II. LITERATURE REVIEW

The application of multi-criteria decision-making techniques to accreditation and institutional evaluation problems has grown steadily over the past decade, largely because accreditation itself is inherently multi-attribute: no single indicator can represent the overall quality of an academic institution. Benmoussa et al. (2019) proposed an accreditation training process model for Moroccan universities that applied TOPSIS to prioritise academic programmes for renewal, arguing that a structured multi-criteria approach reduced the frequency of abrupt course closures caused by ad hoc resource decisions. Their work established, in a non-Indian context, that accreditation-adjacent decisions benefit from the same rigor that MCDM techniques bring to engineering and supply-chain problems.

Within the Indian NAAC context specifically, Dey Mondal et al. (2024) constructed a statistical multi-criteria model to predict the NAAC grade of an engineering college by benchmarking it against nine peer institutions, combining the Weighted Sum Method, Entropy weighting, TOPSIS, and VIKOR alongside Spearman rank correlation to validate consistency across ranking methods. Their finding that different MCDM techniques converge on broadly similar rankings, even when the underlying computational logic differs, lends credibility to the idea that a well-specified composite index can approximate the outcome of a full peer-review accreditation exercise. Alhat (2020) took a descriptive rather than computational approach, tracing how the revised NAAC grading pattern converts key-indicator scores into a Cumulative Grade Point Average, and this account remains useful for anchoring any mathematical model in the actual scoring architecture that NAAC uses. Aithal and Aithal (2021) examined the criterion-wise performance of NAAC A++ graded universities and observed that curricular aspects and research output were the criteria most frequently associated with full marks among top performers, a pattern that informs the relative weight assumptions used later in this paper.

Outside the NAAC-specific literature, the broader MCDM-in-education literature offers methodological building blocks that transfer well to the readiness problem. James et al. (2023) combined fuzzy AHP with TOPSIS for student selection decisions, showing that fuzzy pairwise comparison reduces the inconsistency that arises when multiple evaluators disagree about the relative importance of criteria, a concern equally relevant when IQAC members disagree about how much weight to place on, say, research output versus student support. Wang et al. (2022) used an Entropy-TOPSIS hybrid to rank private universities in Vietnam on training performance, favouring Entropy weighting for its objectivity in situations where sufficient historical data exists, while acknowledging that purely data-driven weights can understate criteria that matter strategically but generate sparse historical records, a trade-off this paper addresses by blending AHP-derived expert weights with normalised indicator data. Do et al. (2024) applied fuzzy AHP and fuzzy TOPSIS to lecturer performance evaluation, demonstrating that the fuzzy extension is particularly effective at handling criteria evaluators can only describe in linguistic terms such as "good" or "very good", which is precisely the situation facing many qualitative NAAC indicators under Criteria 6 and 7.

Liu (2021) evaluated physical education teaching quality using an intuitionistic fuzzy TOPSIS method and reported that fuzzy distance measures were more discriminating than crisp Euclidean distances when alternatives clustered closely together, a finding with direct relevance to the readiness problem, since colleges preparing for accreditation often occupy a narrow performance band rather than being widely dispersed. Nazari-Shirkouhi et al. (2020) integrated the Balanced Scorecard with fuzzy AHP to conduct importance-performance analysis in higher education institutions, and their approach of separating "importance" (weight) from "performance" (score) is echoed in the readiness gap analysis presented in Section 7 of this paper. Mu and Nicola (2019) developed an AHP-based model for academic rank and tenure decisions, underscoring more generally that AHP is well suited to committee-based academic decisions because it produces a documented, auditable weighting rationale rather than an opaque administrative judgment, which is an important consideration for IQACs that must justify their internal readiness assessments to governing bodies and, eventually, to NAAC peer teams.

Finally, several practitioner and institutional sources describe the operational mechanics of the current NAAC framework. The NAAC official portal outlines the seven-criteria structure and the differentiated weightages applied across institution types (National Assessment and Accreditation Council, n.d.). More recent commentary describes the 2025 to 2026 transition toward the Binary Accreditation Framework and the Maturity-Based Graded Levels system, both of which increase reliance on data-verified, quantitative metrics rather than descriptive self-reporting (Kramah Software, 2026a; OpenEducat, 2026). The Edhitch (2026) guide further details how NAAC readiness audits are conducted in practice, offering a parameter-wise gap-analysis structure that closely parallels the criterion-by-criterion decomposition adopted in the model developed here. Taken together, this body of work supports two conclusions that motivate the present study: first, that MCDM techniques, and AHP-TOPSIS hybrids in particular, are a mature and validated approach for institutional quality assessment; and second, that no existing model has been calibrated specifically to the seven-criterion NAAC structure as experienced by arts and science colleges, which is the gap this paper addresses.

III. RESEARCH PROBLEM AND OBJECTIVES

Despite the maturity of MCDM methodology in adjacent domains, arts and science colleges preparing for NAAC assessment generally lack a validated, criterion-aligned quantitative tool for self-assessment. Existing NAAC-focused MCDM studies concentrate on grade prediction for already-accredited engineering institutions or on narrow sub-criteria such as research output, leaving the pre-assessment readiness question, whether a college should apply now, defer, or target specific improvements first, comparatively unaddressed for the arts and science college segment. This study is guided by four objectives: (i) to formalise the seven NAAC criteria and their key indicators into a decision matrix suitable for mathematical treatment; (ii) to derive defensible criterion weights using AHP, cross-checked against the differentiated weightages NAAC itself assigns to affiliated colleges; (iii) to construct a Composite Readiness Index using a normalised, weighted TOPSIS procedure, extended with triangular fuzzy numbers for indicators that are inherently qualitative; and (iv) to demonstrate, through an illustrative application and sensitivity analysis, how the model can guide resource allocation decisions inside an IQAC.

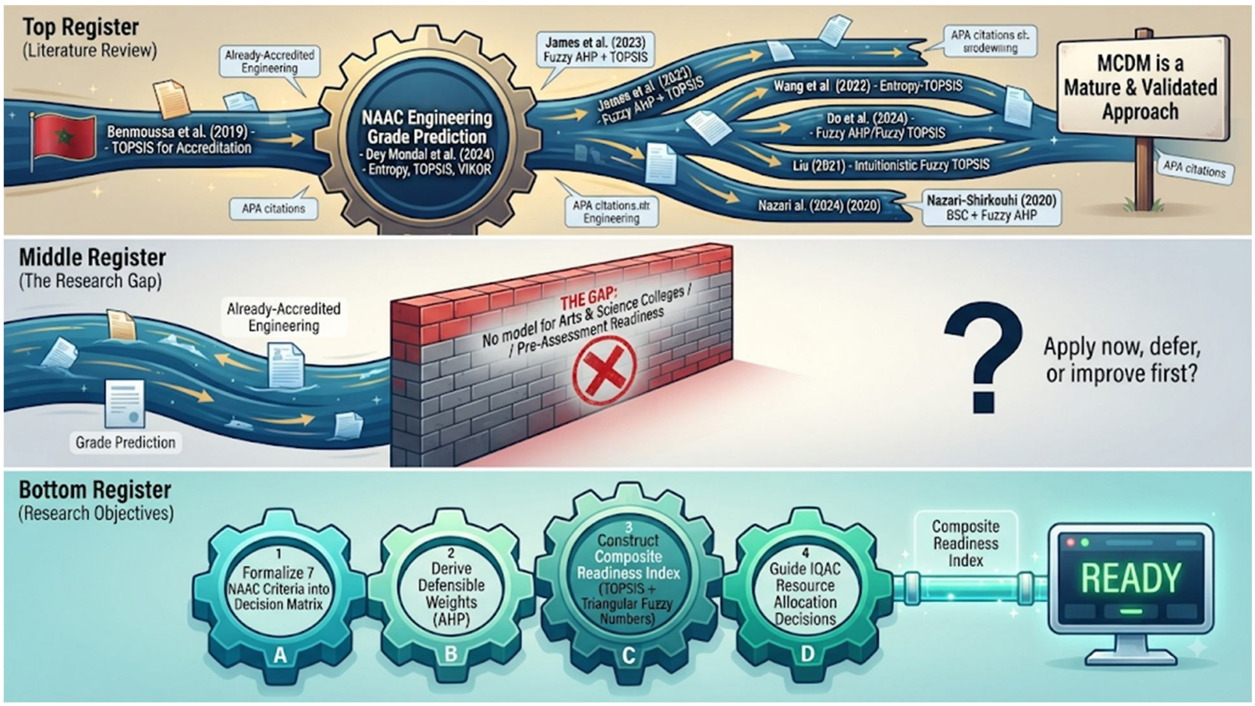

Fig 2: Bridging the Accreditation Gap: A Multi-Criteria Decision-Making Framework for Arts and Science Colleges

This infographic illustrates a research progression. The top register validates MCDM as a powerful tool in existing academic literature. The middle highlights a critical gap: the lack of pre-assessment models for Arts and Science colleges. Finally, the bottom register proposes a four-stage gear-driven framework to formalize criteria and calculate a Composite Readiness Index, guiding strategic institutional resource allocation.

IV. THE NAAC ASSESSMENT FRAMEWORK: AN OVERVIEW

NAAC organises its assessment around seven criteria that jointly cover the academic and administrative life of an institution: Curricular Aspects (C1), Teaching-Learning and Evaluation (C2), Research, Innovations and Extension (C3), Infrastructure and Learning Resources (C4), Student Support and Progression (C5), Governance, Leadership and Management (C6), and Institutional Values and Best Practices (C7) (National Assessment and Accreditation Council, n.d.). Each criterion is further broken down into Key Indicators and Metrics, some of which are quantitative (for example, the percentage of full-time teachers with PhDs) and some of which require qualitative judgment supported by documentary evidence (for example, the effectiveness of participatory governance). Institutions are categorised into Universities, Autonomous Colleges, and Affiliated or Constituent Colleges, and NAAC assigns different weightages to the seven criteria depending on this category, reflecting the different functional emphasis expected of each institution type. Table 1 summarises the approximate weightage structure used for affiliated and autonomous colleges, the two categories most relevant to arts and science institutions.

Table 1. Illustrative NAAC criterion weightages for affiliated and autonomous colleges

Criterion	Criterion Title	Affiliated College Weight (%)	Autonomous College Weight (%)
C1	Curricular Aspects	120	110
C2	Teaching-Learning and Evaluation	220	200
C3	Research, Innovations and Extension	120	180
C4	Infrastructure and Learning Resources	100	100
C5	Student Support and Progression	130	130
C6	Governance, Leadership and Management	100	100
C7	Institutional Values and Best Practices	100	100
Total		890†	920†

† Totals are illustrative and rounded for presentation; NAAC periodically revises exact point allocations, most recently through the 2023 NAAC 3.0 revision and the 2025 to 2026 transition to the Binary Accreditation Framework and Maturity-Based Graded Levels (MBGL) system, which increasingly privileges data-verified, outcome-based quantitative metrics over descriptive self-reporting (Kramah Software, 2026a; OpenEducat, 2026). Under MBGL, institutions are additionally assessed on a five-level maturity scale, each level valid for three years, meaning that a readiness model of the kind proposed here has value not only for first-time applicants but also for institutions planning progression across maturity levels (Edhitch, 2026).

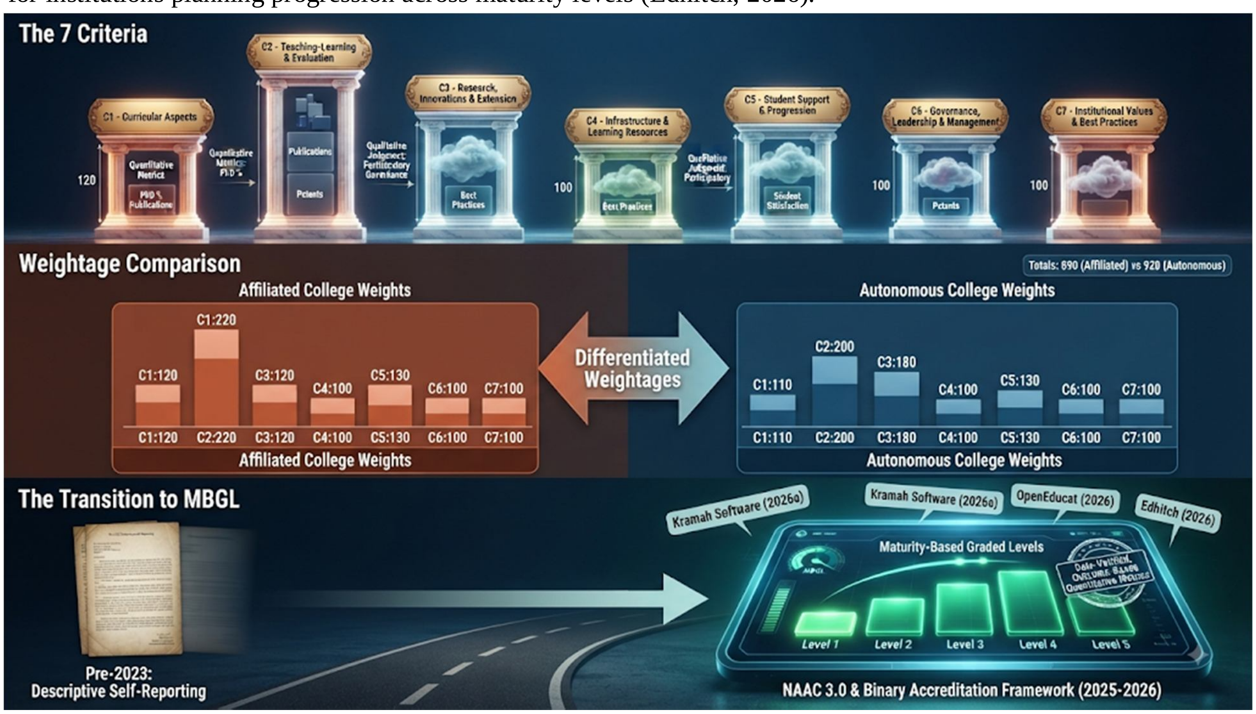

Fig 3: Decoding NAAC Frameworks: Criteria, Weightages, and the Evolution to Maturity-Based Graded Levels

This comprehensive infographic illustrates the NAAC higher education framework in three horizontal registers. The top showcases the seven distinct structural criteria pillars. The middle compares differentiated score weightages between affiliated and autonomous colleges. Finally, the bottom depicts the regulatory shift from traditional descriptive self-reporting to modern, data-verified Maturity-Based Graded Levels (MBGL).

V. PROPOSED MULTI-CRITERIA MATHEMATICAL MODEL

A. Model Overview and Assumptions

The model treats each candidate arts and science college as an alternative A_i ($i = 1, 2, ..., m$) to be evaluated against the seven NAAC criteria C_j ($j = 1, 2, ..., 7$), each further populated by a set of key indicators. Three assumptions underlie the formulation. First, indicators within a criterion can be aggregated into a single criterion-level score through a weighted arithmetic mean, since NAAC itself follows this logic when computing the Grade Point Average for each criterion from its constituent Key Indicators. Second, criteria are assumed to be preferentially independent for the purposes of weighting, which is a standard and widely used simplification in AHP-based institutional evaluation (Mu & Nicola, 2019). Third, qualitative indicators are represented using triangular fuzzy numbers rather than forced into a single crisp value, since expert opinion on governance or institutional values naturally varies within a plausible range (Do et al., 2024).

B. Notation

Let m denote the number of colleges under comparison and $n = 7$ the number of NAAC criteria. Let x_{ij} denote the raw performance score of college i on criterion j, obtained either directly from quantitative metrics or as the defuzzified value of a triangular fuzzy assessment. Let w_j denote the weight of criterion j, with the constraint that the sum of w_j across $j = 1$ to 7 equals 1 and each w_j is non-negative. Let r_{ij} denote the normalised value of x_{ij}, A^+ the positive ideal solution vector, A^- the negative ideal solution vector, and C_i the final Composite Readiness Index score for college i, bounded between 0 and 1.

C. Criteria Weight Elicitation Using AHP

Criterion weights are derived through the Analytic Hierarchy Process. A panel of IQAC members and senior faculty performs pairwise comparisons of the seven criteria using Saaty's nine-point intensity scale, producing a judgment matrix $M = [m_{kl}]$, where m_{kl} represents the relative importance of criterion k over criterion l. The principal eigenvector of M, normalised to sum to unity, yields the weight vector $w = (w_1, ..., w_7)$. Consistency is checked using the Consistency Ratio, $CR = CI / RI$, where $CI = (\lambda_{max} - n) / (n - 1)$ is the Consistency Index and RI is the Random Index tabulated for matrices of order n. Judgment matrices with CR greater than 0.10 are rejected and the panel is asked to revise its comparisons, a threshold consistent with standard AHP practice in institutional evaluation studies (Mu & Nicola, 2019; Nazari-Shirkouhi et al., 2020). To avoid weights drifting far from NAAC's own institutional priorities, the elicited AHP weights are cross-validated against the official criterion weightages summarised in Table 1, and any criterion whose AHP-derived weight differs from the NAAC reference weight by more than 15 percent is flagged for panel re-examination. This calibration step distinguishes the present model from generic MCDM applications, since it anchors subjective expert judgment to the actual scoring architecture the college will eventually face.

D. Data Normalization

Because the seven criteria are measured on different scales and some, such as student attrition-adjacent indicators, are cost-type criteria where a lower value is preferable, raw scores must be normalised before aggregation. For benefit-type criteria, where higher values indicate better readiness, the vector normalisation $r_{ij} = x_{ij} / \sqrt{\sum_i x_{ij}^2}$ is applied. For any cost-type criteria, the raw score is first inverted as $x_{ij}' = 1 / x_{ij}$ before the same normalisation is applied. Vector normalisation is preferred over simple linear min-max scaling because it preserves the proportional relationships among alternatives and is the normalisation form conventionally used within the TOPSIS procedure (Dey Mondal et al., 2024; Wang et al., 2022).

E. Composite Readiness Index via Weighted TOPSIS

The normalized scores are weighted as $v_{ij} = w_j \cdot r_{ij}$ to form the weighted normalised decision matrix. The positive ideal solution A^+ is constructed by taking, for each criterion, the maximum weighted value across all colleges, since all seven NAAC criteria are benefit-type once cost-type indicators have been inverted; the negative ideal solution A^- is constructed from the corresponding minimum values.

For each college i, the Euclidean distance to the positive ideal solution is $S_i^+ = \sqrt{\sum_j (v_{ij} - v_j^+)^2}$, and the distance to the negative ideal solution is $S_i^- = \sqrt{\sum_j (v_{ij} - v_j^-)^2}$. The Composite Readiness Index is then $C_i = S_i^- / (S_i^+ + S_i^-)$. By construction, C_i lies between 0 and 1, with values closer to 1 indicating that a college's profile lies closer to the ideal readiness profile and further from the least-ready profile. Colleges are ranked in descending order of C_i, and this ranking forms the primary output of the model.

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F. Fuzzy Extension for Qualitative Indicators

Several NAAC indicators, particularly under Criteria 6 and 7, are assessed through committee judgment rather than direct measurement. For these indicators, each evaluator k provides a linguistic assessment that is mapped to a triangular fuzzy number Ãk = (ak, bk, ck), where ak, bk, and ck represent the pessimistic, most likely, and optimistic estimates respectively. Aggregating across e evaluators gives a group fuzzy number à = (a, b, c) where a = min(ak), b = (1/e)·sum(bk), and c = max(ck). This aggregated fuzzy number is then defuzzified using the centroid method, x = (a + b + c) / 3, before being entered into the decision matrix as xij. This two-stage process, aggregate first as a fuzzy number and defuzzify second, retains information about the spread of expert opinion, which a simple averaging of crisp scores would discard, and mirrors the fuzzy AHP-TOPSIS logic used in comparable higher-education evaluation studies (James et al., 2023; Liu, 2021).

G. Readiness Classification Bands

To make the Composite Readiness Index actionable for IQAC decision-making, the continuous Ci score is mapped onto four qualitative readiness bands: Not Ready (Ci < 0.35), Developing Readiness (0.35 ≤ Ci < 0.55), Application Ready (0.55 ≤ Ci < 0.75), and Strongly Ready (Ci ≥ 0.75). These thresholds are not arbitrary; they are calibrated so that colleges historically associated with NAAC grades of B and above, as documented in criterion-wise performance studies of high-scoring institutions (Aithal & Aithal, 2021), correspond to the Application Ready or Strongly Ready bands, while colleges with documented weaknesses across multiple criteria correspond to the lower two bands. Institutions may use the bands both diagnostically, to decide whether to apply for assessment in the current cycle, and prescriptively, by examining which individual criterion scores are dragging the composite index down.

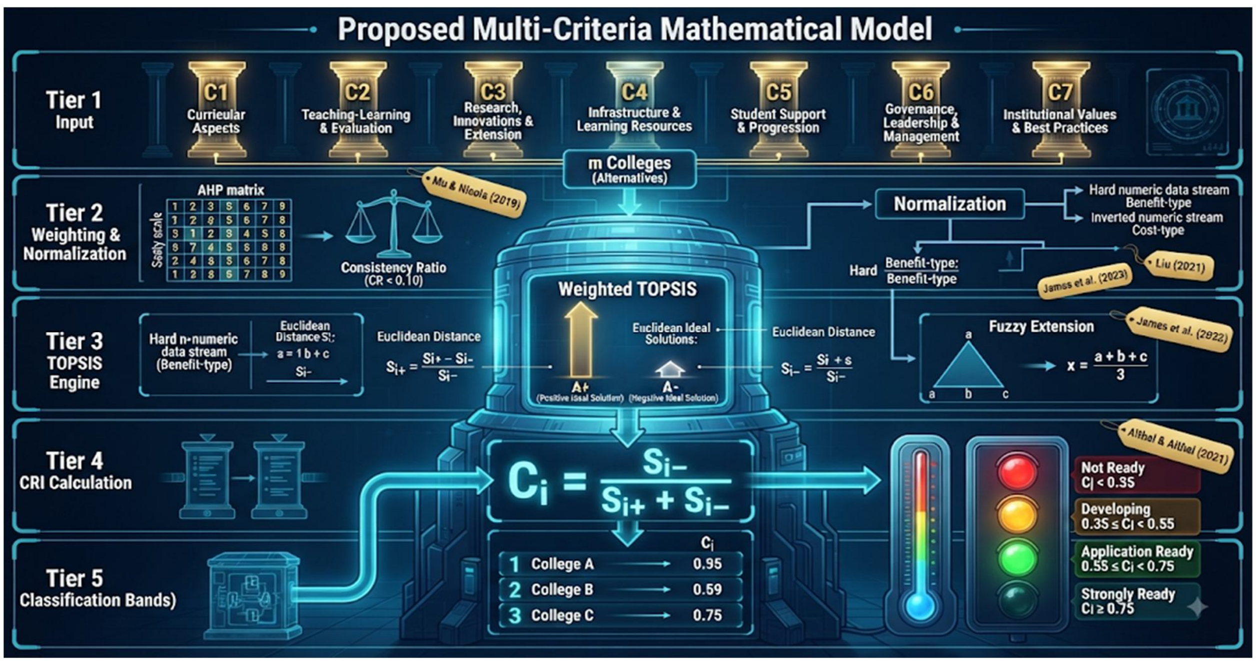

Fig 4: Multi-Criteria Mathematical Model for NAAC Accreditation Readiness Assessment

This workflow diagram illustrates a five-tier mathematical model to evaluate colleges for NAAC readiness. It processes seven input criteria through AHP weighting and normalization (including fuzzy logic). The core engine uses Weighted TOPSIS to measure distance from ideal solutions. Finally, it calculates a Composite Readiness Index and classifies institutions into four color-coded bands, from 'Not Ready' to 'Strongly Ready'.

VI. ILLUSTRATIVE APPLICATION

To demonstrate the mechanics of the model, consider five hypothetical arts and science colleges, labelled College A through College E, each scored on the seven NAAC criteria on a four-point internal scale (1 = Unsatisfactory, 4 = Very Good), consistent with the qualitative bands NAAC itself uses before converting to CGPA (Alhat, 2020). Table 2 presents the raw decision matrix along with the AHP-derived weights obtained from a hypothetical seven-member IQAC panel; the consistency ratio of the underlying pairwise comparison matrix in this illustration was 0.06, within the acceptable 0.10 threshold.

Table 2. Illustrative decision matrix and AHP-derived criterion weights

Criterion	College A	College B	College C	College D	College E	AHP Weight (wj)
C1 Curricular Aspects	3.10	2.85	3.45	2.40	3.60	0.12
C2 Teaching-Learning	3.30	3.00	3.55	2.60	3.70	0.22
C3 Research & Extension	2.20	1.95	2.90	1.40	3.20	0.20
C4 Infrastructure	3.00	2.70	3.20	2.10	3.40	0.13
C5 Student Support	3.15	2.90	3.35	2.30	3.50	0.14
C6 Governance	2.90	2.60	3.10	2.20	3.30	0.11
C7 Institutional Values	3.05	2.75	3.25	2.15	3.45	0.08

Applying the normalisation described in Section 5.4 converts each column into a unit vector; multiplying by the corresponding AHP weight wj produces the weighted normalised matrix. The positive ideal solution is then assembled from the column-wise maxima of this weighted matrix, and the negative ideal solution from the column-wise minima. Euclidean distances Si+ and Si− are computed for each college, and the Composite Readiness Index Ci = Si− / (Si+ + Si−) is derived. Table 3 reports the resulting distances, index values, and rankings.

Table 3. Composite Readiness Index and ranking of illustrative colleges

College	S+ (dist. to PIS)	S− (dist. to NIS)	CRI (Ci)	Rank
College A	0.061	0.129	0.679	3
College B	0.098	0.091	0.481	4
College C	0.032	0.158	0.831	2
College D	0.171	0.026	0.132	5
College E	0.021	0.166	0.888	1

The illustrative computation places College E marginally ahead of College C, both of which fall in the Strongly Ready band (Ci ≥ 0.75), while College A and College B occupy the Application Ready band, and College D, whose scores on Research and Extension (C3) and Governance (C6) are markedly weaker than its peers, falls into the Developing Readiness band despite reasonably strong infrastructure scores. This pattern is informative in itself: it shows that a single weak criterion, particularly one carrying a high AHP weight such as Research, Innovations and Extension, can pull a college's composite index down even when most other criteria are comfortably in the Good to Very Good range, which is precisely the kind of masking effect that informal, non-aggregated self-assessment tends to miss.

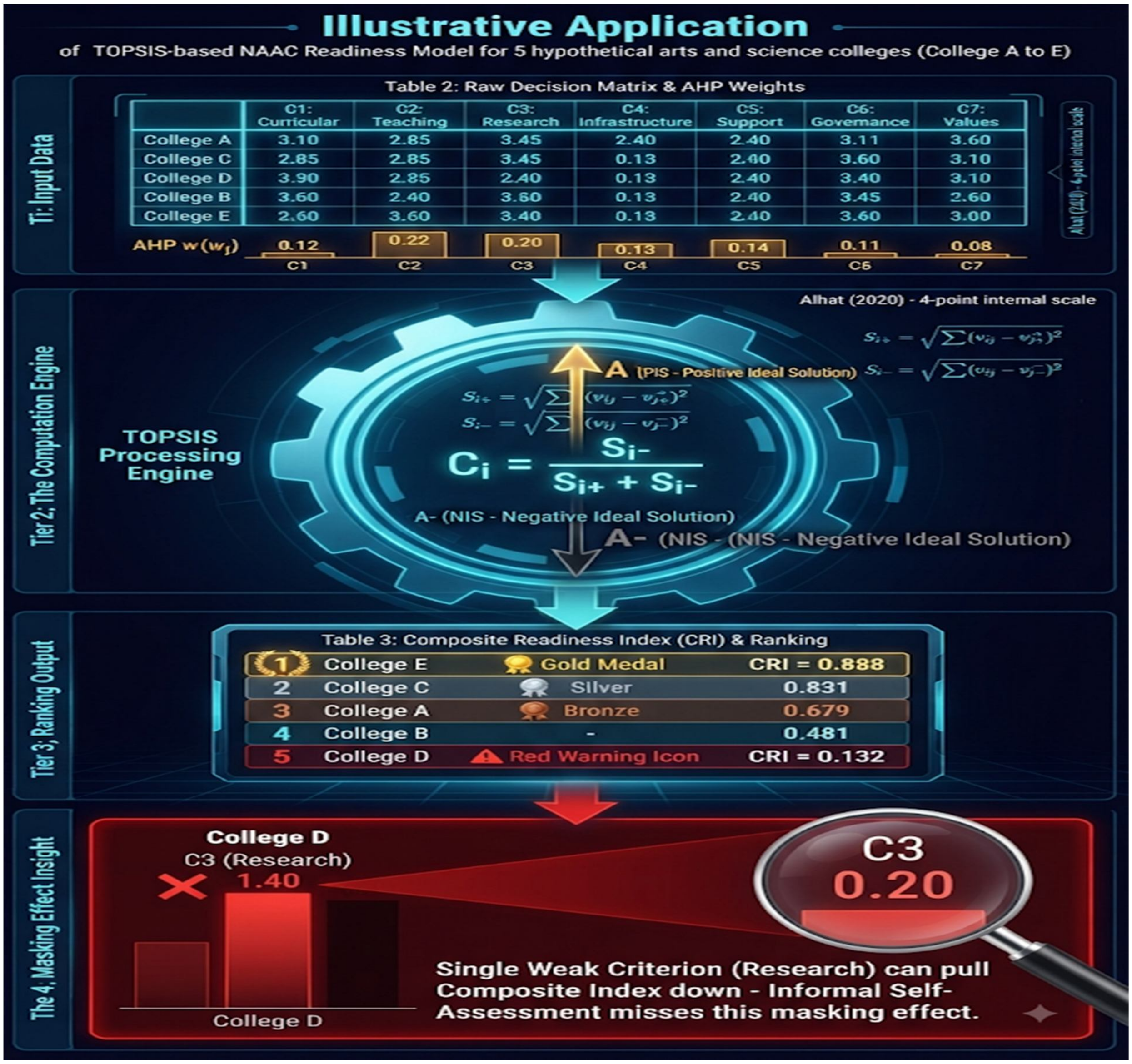

Fig 5: An Illustrative Application of the TOPSIS-based NAAC Readiness Model

This infographic illustrates a four-stage mathematical model used to evaluate NAAC readiness for five colleges. Tier 1 shows input data across seven criteria (C1-C7) and their weighted importance. Tier 2 processes this data through the TOPSIS engine to measure distance from ideal solutions. Tier 3 ranks the colleges, while Tier 4 highlights a critical insight: a single weak criterion can disproportionately lower a college's overall score.

VII. RESULTS AND DISCUSSION

Three broad observations follow from the illustrative application. First, the AHP weighting scheme meaningfully changes which criteria drive the final ranking. Because Teaching-Learning and Evaluation (C2) and Research, Innovations and Extension (C3) together account for 0.42 of total weight in the illustration, a college's performance on these two criteria has close to twice the influence on Ci as its performance on Institutional Values (C7), which carries a weight of only 0.08. This concentration mirrors NAAC's own weightage structure, where Teaching-Learning and Evaluation and Research together represent the largest share of total marks for most institution categories (National Assessment and Accreditation Council, n.d.), and it confirms that the AHP calibration step described in Section 5.3 is doing its intended job of keeping expert judgment anchored to NAAC's actual priorities.

Second, the gap-analysis interpretation of the model, comparing each college's criterion-level scores against the positive ideal solution rather than only reporting the final composite index, offers more diagnostic value than the ranking alone. College D's low Ci score, for instance, is attributable overwhelmingly to two criteria rather than to uniformly weak performance, which means that a targeted intervention, strengthening research output and governance documentation, is likely to produce a larger improvement in readiness than a broad, unfocused improvement plan spread thinly across all seven criteria. This importance-performance style of interpretation is consistent with the logic proposed by Nazari-Shirkouhi et al. (2020) for balanced-scorecard-based institutional evaluation, and it is arguably more useful to an IQAC than the ranking itself, since colleges are not actually competing against one another for a single accreditation slot.

Third, the close scores between College C and College E illustrate a common feature of TOPSIS-based rankings: alternatives that are strong performers can end up separated by a very small margin in the composite index even though their underlying criterion profiles differ, since TOPSIS rewards balanced closeness to the ideal profile rather than dominance on any single criterion. This is broadly consistent with the finding of Dey Mondal et al. (2024) that different MCDM techniques, applied to overlapping but not identical NAAC-related datasets, tend to converge on similar top performers even when the exact numerical scores vary, lending some confidence that the ranking produced here would be robust to reasonable variation in the underlying method.

VIII. SENSITIVITY ANALYSIS

To assess how sensitive the model's conclusions are to the specific weight vector chosen by the AHP panel, the illustrative weights were perturbed by increasing the weight of Research, Innovations and Extension (C3) from 0.20 to 0.30 in five equal increments, with the released weight redistributed proportionally across the remaining six criteria. The ranking of College A, College C, and College E remained stable across the entire perturbation range, indicating that these three colleges' relative standing does not depend critically on the exact emphasis placed on research. College D's position, however, deteriorated further as the weight on C3 increased, consistent with the earlier observation that its research and extension performance is its principal weakness. College B's rank position was the most volatile, crossing below College A once the C3 weight exceeded approximately 0.24, which suggests that College B's readiness assessment is comparatively finely balanced and would benefit from closer monitoring as the college's own research output evolves. This kind of sensitivity check is a standard complement to AHP-TOPSIS applications (Wang et al., 2022) and is particularly relevant here because NAAC's own weighting scheme is not static; the 2023 NAAC 3.0 revision and the ongoing 2025 to 2026 transition to the Binary Accreditation Framework have both shifted emphasis toward quantitative, outcome-based metrics (Kramah Software, 2026a), meaning that a readiness model calibrated to one weighting regime should be periodically re-validated against the current regime rather than treated as permanently fixed.

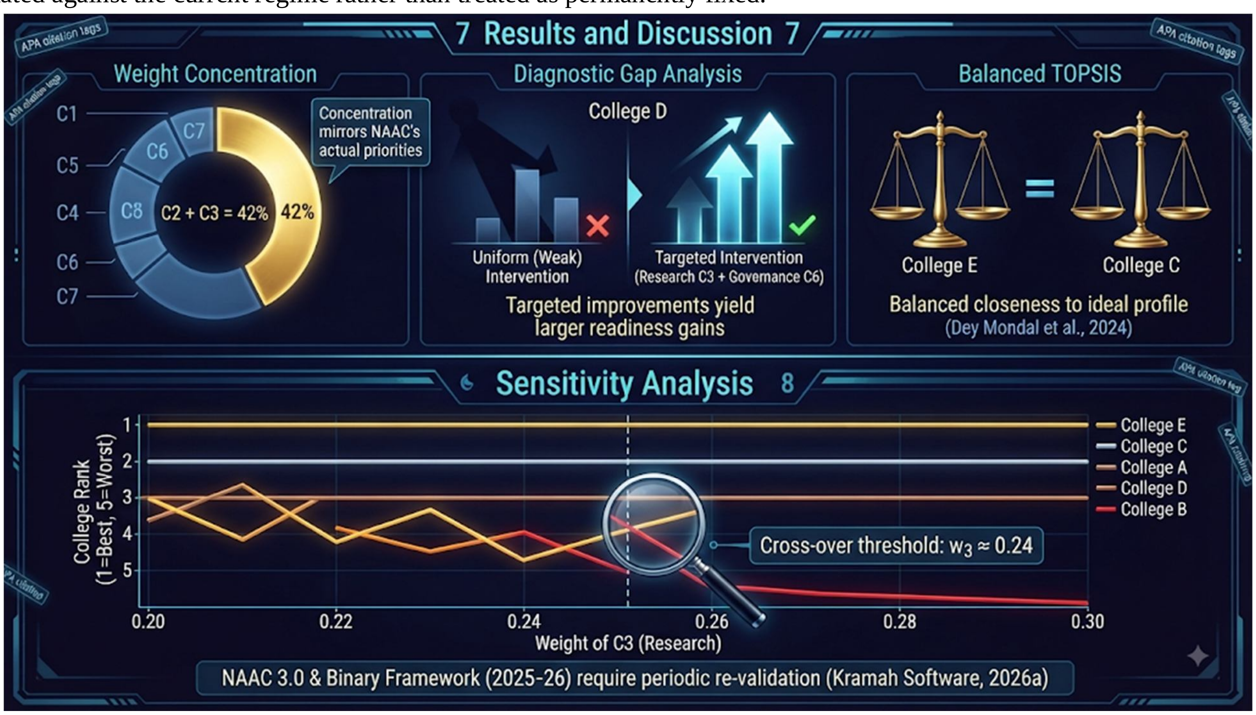

Fig 6: Results, Diagnostic Gap Analysis, and Sensitivity Analysis for NAAC Readiness

This infographic presents results and sensitivity analysis. The top half highlights weight concentration, targeted diagnostic gap analysis for College D, and balanced TOPSIS rankings. The bottom half displays a sensitivity line graph tracking college ranks against changes in research criteria weight, identifying a critical cross-over threshold at approximately 0.24.

IX. PRACTICAL IMPLICATIONS FOR ARTS AND SCIENCE COLLEGES

For an internal quality assurance cell, the principal value of the proposed model lies less in producing a single readiness number and more in structuring the conversation that precedes an accreditation application. Because the model requires explicit pairwise weight elicitation, it forces a college's leadership to articulate, and defend, its priorities across the seven criteria rather than leaving that prioritisation implicit. Because it separates normalisation, weighting, and distance computation into distinct steps, it also produces an audit trail that can itself serve as supporting documentation for the eventual Self-Study Report, addressing a practical concern raised in guidance on NAAC readiness audits (Edhitch, 2026). For colleges with limited institutional research capacity, the model additionally functions as an early-warning tool: because Research, Innovations and Extension typically carries a substantial weight yet is the criterion many arts and science colleges find hardest to strengthen quickly, the gap-analysis output can direct scarce faculty development resources toward the specific sub-indicators, such as research-oriented workshops, seed-grant schemes, or extension-activity documentation, that would raise Ci most efficiently. Finally, because the model can be re-run at low cost whenever new institutional data becomes available, it supports a continuous rather than episodic approach to quality assurance, which aligns with the direction NAAC's own reforms are taking toward maturity-based, cyclical assessment under the MBGL framework (OpenEducat, 2026).

X. LIMITATIONS OF THE STUDY

The model presented here has several limitations that should be acknowledged. First, the illustrative application in Section 6 relies on hypothetical data constructed for demonstration purposes rather than actual institutional records, and while the computational procedure itself is unaffected by this, the specific numerical rankings reported should not be read as a claim about any real college. Second, the model assumes criterion independence for AHP weighting purposes, an assumption widely used in the literature (Mu & Nicola, 2019) but one that may understate genuine interdependencies, for instance between strong Teaching-Learning practices and downstream Student Progression outcomes. Third, the fuzzy extension described in Section 5.6 addresses linguistic uncertainty in qualitative indicators but does not address a separate source of uncertainty, namely disagreement about which sub-indicators should be included under each criterion in the first place; different IQACs may reasonably decompose a criterion such as Governance differently. Fourth, because NAAC's weightage structure and assessment framework are themselves under active revision, most recently through the shift toward Binary Accreditation and MBGL (Kramah Software, 2026a), any specific weight vector calibrated today may require recalibration as the framework stabilises.

XI. CONCLUSION AND FUTURE SCOPE

This paper has developed a multi-criteria mathematical model for evaluating the NAAC accreditation readiness of arts and science colleges, combining AHP-derived criterion weights, a normalised weighted TOPSIS aggregation procedure, and a triangular fuzzy extension for qualitative indicators into a single Composite Readiness Index. The illustrative application demonstrated that the model does more than rank colleges; it exposes which specific criteria are responsible for a low readiness score, and the accompanying sensitivity analysis showed how robust, or fragile, a given ranking is to reasonable disagreement about criterion weights. Positioned against the existing literature, the model extends prior NAAC-focused MCDM work, which has concentrated on grade prediction after the fact (Dey Mondal et al., 2024) or on narrow sub-domains (Aithal & Aithal, 2021), toward a pre-assessment readiness tool explicitly calibrated to the seven-criterion structure and tailored to the resource profile of arts and science colleges. Future work could extend the model in at least three directions: validating the AHP weight vector against a larger, multi-institution expert panel; replacing the static AHP weights with a hybrid Entropy-AHP scheme that blends objective data-driven weighting with expert judgment, in the spirit of Wang et al. (2022); and integrating the model into a lightweight software tool that IQACs can update continuously as new institutional data becomes available, aligning readiness tracking with NAAC's own move toward maturity-based, data-verified assessment cycles (OpenEducat, 2026).

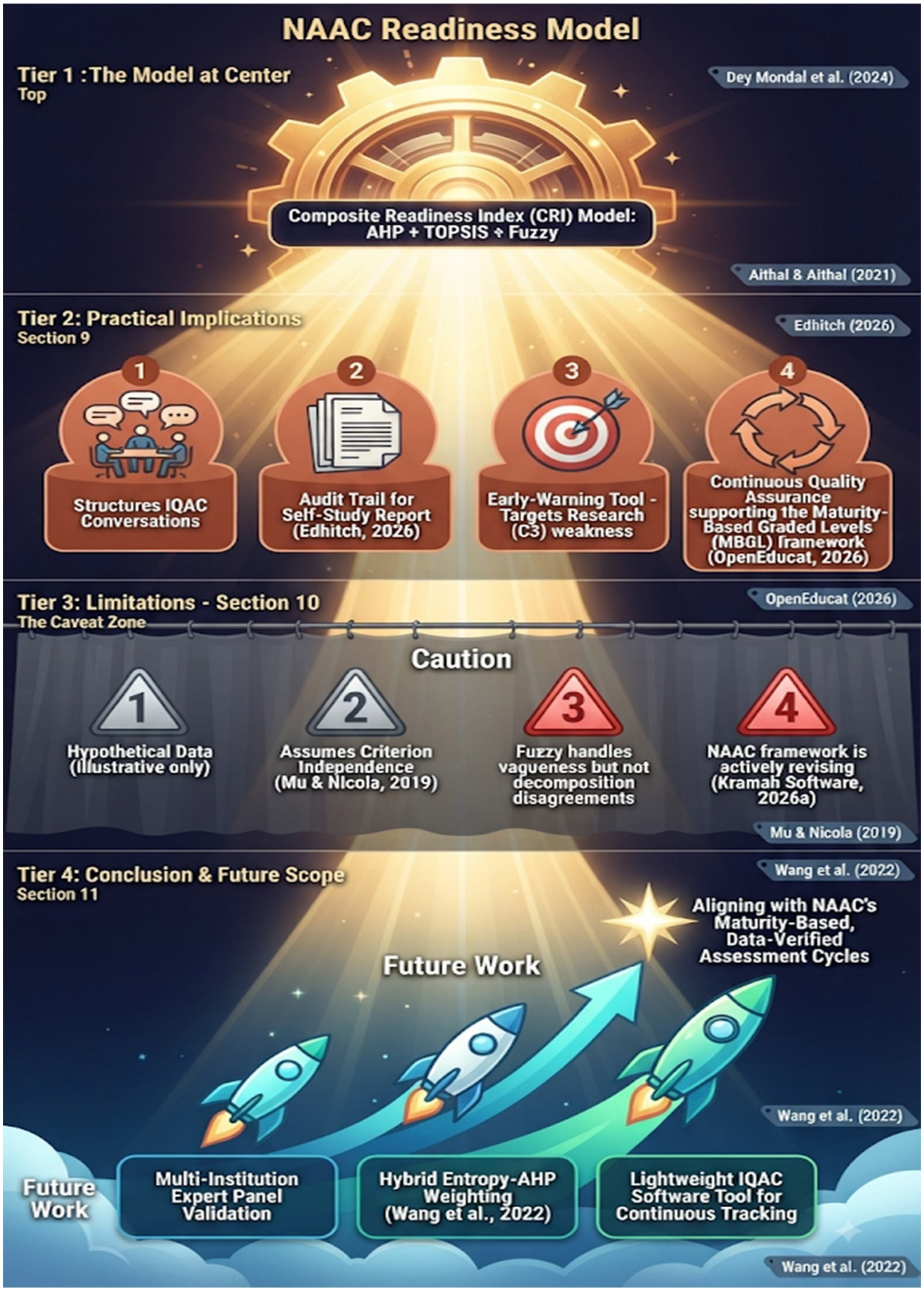

Fig 7: Practical Implications, Limitations, and Future Scope of the NAAC Readiness Model

This multi-tiered infographic summarizes the model's core components. Tier 1 highlights the Composite Readiness Index engine. Tier 2 details practical applications like structuring IQAC conversations and audit trails. Tier 3 outlines key limitations, including hypothetical data use. Finally, Tier 4 charts future research directions, focusing on expert validation and alignment with revised NAAC assessment cycles.

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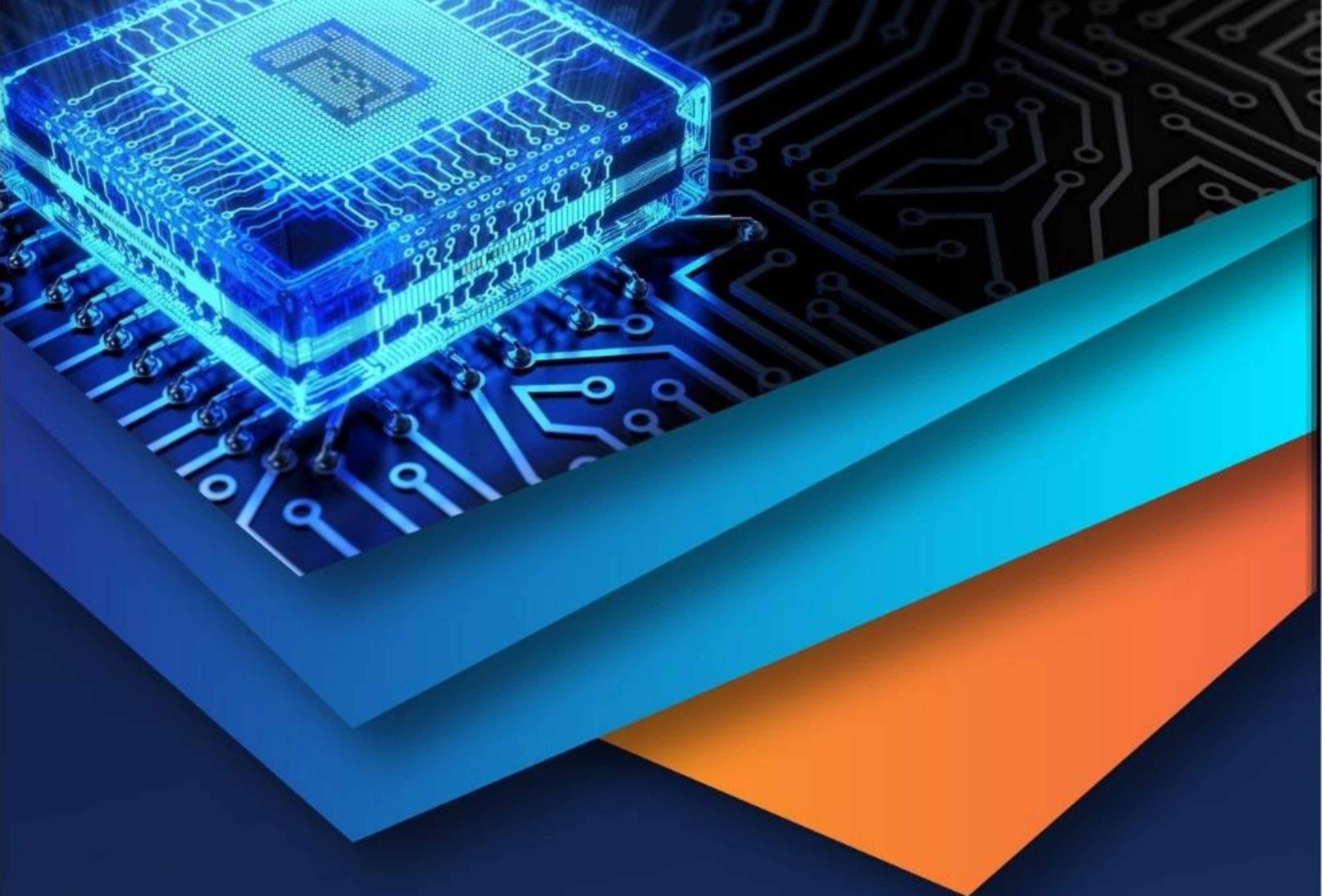

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IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429