iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VII Month of publication: July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84403

www.ijraset.com
Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Transformation of Engineering Education in India (2015–2026): A Data-Driven Analysis of Admissions, Employability, Faculty Well-being, and the Rise of AI-Driven Disciplines

Kirankumar B[1], Navaneeth I M[2] Vittal Bhat M[3]
[1,2]Departent of Mechanical Engineering, P. A. College of Engineering (PACE), Mangaluru, Karnataka, India – 574153 and Affiliated to Visvesvaraya Technological University.
[3]Department of Electronics and Communication Engineering, P. A. College of Engineering (PACE), Mangaluru, Karnataka, India – 574153 and Affiliated to Visvesvaraya Technological University.

Abstract: India's engineering education system underwent its most turbulent twelve-year period since liberalisation between 2015 and 2026: undergraduate intake fell from roughly 17 lakh approved seats in 2014-15 to a decade low near 12.5 lakh in 2021-22, before rebounding to about 14.9 lakh in 2024-25 and an approved 15.98 lakh across 5,875 AICTE-recognised colleges for 2025-26, driven almost entirely by demand for computer science, artificial intelligence (AI), and data-science programmes while core branches such as civil and mechanical engineering continued to lose share. Parallel to this reallocation, employability estimates from national skill-assessment surveys rose from roughly one-third of graduates in the mid-2010s to a peak near 71.5% in 2025 before easing slightly to 70.15% in the India Skills Report 2026, with computer-science and IT graduates reporting employability of 80% and 78% respectively and women's employability (54%) overtaking men's (51.5%) for the first time in five years; independent hiring-outcome studies nonetheless suggest that only a minority of graduates secure engineering-relevant employment in their graduation year, revealing a persistent gap between assessed employability and realised employment. At the same time, mounting evidence of faculty vacancy rates exceeding 40-50% in several states, heavy reliance on ad hoc guest faculty, and emerging work-life-imbalance research signal a well-being crisis among engineering educators that has received comparatively little empirical attention relative to student-facing metrics. This paper proposes a PRISMA-guided systematic literature review combined with an explanatory sequential mixed-methods design to model the structural relationships among admissions capacity, curricular AI-orientation, faculty well-being, and graduate employability across the 2015-2026 period, using nationally representative administrative datasets (AICTE, AISHE, NIRF), placement and skills-assessment reports through the India Skills Report 2026, and a purpose-built faculty/student survey. The analytical plan combines descriptive time-series analysis, multiple regression, exploratory and confirmatory factor analysis, structural equation modelling, and machine-learning forecasting (ARIMA/SARIMA, Random Forest, XGBoost) to both explain past dynamics and forecast enrolment, discipline-mix, and employability trajectories to 2030. We outline expected findings, policy implications for seat-capacity regulation, faculty recruitment, and curriculum reform, and a research agenda addressing regional and gender disparities, teaching-load-linked well-being, and the sustainability of the current AI-disciplinary boom.
Keywords: engineering education policy; AICTE; AISHE; NIRF; graduate employability; faculty well-being; artificial intelligence curriculum; structural equation modelling; India higher education

I. INTRODUCTION

India operates the largest technical higher-education system in the world by enrolment, with several thousand AICTE-approved engineering institutions and, historically, more than a million approved undergraduate seats per year. The period spanning 2015 to 2026 represents a natural policy experiment: a demand contraction that forced seat cuts and institutional closures in the late 2010s, followed by a sharp, AI- and computer-science-led recovery in the early-to-mid 2020s that continued into 2026. Approved undergraduate engineering intake fell from about 17.05 lakh seats in 2014-15 and 16.30 lakh in 2015-16 to a decade low of roughly 12.5 lakh in 2021-22, before AICTE lifted long-standing seat caps and intake rebounded to about 14.9 lakh in 2024-25 and 15.98 lakh approved across 5,875 recognised colleges for the 2025-26 session, a 7% year-on-year rise.

©IJRASET: All Rights are Reserved

Crucially, this rebound has been structurally uneven: computer science, AI, data science, and allied disciplines have absorbed the overwhelming majority of new capacity, while several states (Telangana's restriction upheld by the High Court in May 2025, Karnataka considering similar limits) have begun actively restricting further computer-science expansion even as core branches such as civil and mechanical engineering continue to show comparatively weak enrolment and employability.

This restructuring of the supply side has occurred alongside contested claims about graduate outcomes. National skill-assessment exercises report headline engineering employability rising from roughly one-third of graduates a decade ago to a peak of 71.5% in the 2025 edition, easing slightly to 70.15% in the India Skills Report 2026 — described by its authors as reflecting stability in technical domains despite rising specialisation demands — with computer-science and IT graduates reporting employability of 80% and 78% respectively and AI/ML-linked hiring recording roughly 600% growth. The 2026 edition also records a first-in-five-years reversal in the gender employability gap, with women's employability (54%) overtaking men's (51.5%), alongside a decline in MBA employability to 72.76% and persistently low employability for ITI (45.95%) and polytechnic (32.92%) graduates. Yet independent hiring-outcome research paints a far less optimistic picture, with some industry-run talent surveys finding that a large majority of a recent graduating cohort received no job or internship offer at all. This divergence between assessed "employability" (skill-test performance) and realised "employment" (actual hiring outcomes) is itself an under-theorised empirical puzzle that this paper treats as a central research problem.

A third, comparatively neglected dimension of this transformation is the well-being and adequacy of the faculty workforce that must deliver this expanded and increasingly AI-oriented curriculum. Reports from multiple states describe engineering faculty vacancy rates above 40-50%, recruitment freezes dating back over a decade in some government colleges, and a national shortfall of several lakh teaching positions across higher education. A small but growing literature on work-life imbalance and burnout among Indian private-college faculty suggests that expansion has occurred without commensurate investment in the human capital that sustains it. This paper's third research strand therefore asks how administrative expansion and curricular change during 2015-2026 have affected faculty workload, well-being, and retention, and how these, in turn, feed back into graduate outcomes.

Taken together, the admissions, employability, faculty well-being, and AI-disciplinary-shift strands are rarely modelled jointly. Existing studies tend to examine one dimension using descriptive statistics from a single data source and a short time window. This paper contributes (a) an integrated conceptual framework linking these four strands, (b) a PRISMA-guided systematic review protocol synthesising the fragmented empirical literature, (c) a mixed-methods research design combining decade-long administrative panel data with primary survey and interview data, and (d) a full statistical and machine-learning analysis plan capable of both explanatory modelling (regression, factor analysis, SEM) and forecasting (time-series and ML methods) through 2030.

II. LITERATURE REVIEW

A. Admissions and Capacity Dynamics in Indian Technical Education

Administrative data from AICTE show that undergraduate engineering intake is highly elastic to perceived labour-market returns and to regulatory posture. The 2014-2022 contraction — often described in trade press as a decade-long decline — coincided with a moratorium on new engineering colleges and permission for institutions to surrender unfilled seats, with over five and a half lakh seats cut or surrendered between 2019 and 2022 alone. The subsequent 2022-2026 recovery followed the lifting of seat caps, introduction of supernumerary seats for working professionals, and a pronounced reallocation of capacity toward computer science, AI, data science, cybersecurity, and allied "new-age" branches, with several states (Tamil Nadu, Andhra Pradesh, Telangana) accounting for a disproportionate share of new seat growth. This pattern is consistent with signalling-theory and human-capital accounts of enrolment behaviour, in which students and families respond to perceived returns to specific credentials rather than to engineering education as an undifferentiated category.

B. Employability and the Skills Gap

The India Skills Report series (Wheebox/ETS, CII, AICTE, AIU) is the most widely cited longitudinal source on engineering employability, showing a rise from roughly one-third in 2014 to a peak of 71.5% in the 2025 edition before easing to 70.15% in the 13th (2026) edition, with computer-science and IT graduates reporting the highest employability (80% and 78% respectively) and civil engineering historically the lowest. The 2026 edition further reports that women's employability (54%) overtook men's (51.5%) for the first time in five years, that MBA employability declined to 72.76% from 78% the previous year, and that ITI and polytechnic graduates continue to lag substantially (45.95% and 32.92% respectively) despite ongoing skilling initiatives. However, these figures measure standardised test-based "employability," not realised employment.

Contemporaneous hiring-outcome research — including talent-platform reports and labour-force survey (PLFS)-based estimates — suggests substantially lower rates of actual job or internship attainment among recent graduates, with combined unemployment-and-underemployment estimates for educated youth reported in a considerably higher range than headline unemployment figures. This employability-employment gap, and its concentration in core branches versus computing-adjacent branches, motivates this paper's regression and SEM specifications.

C. Faculty Well-being and Institutional Capacity

Faculty adequacy is a binding constraint on quality assurance: AICTE's own approval norms specify faculty-student ratio benchmarks, and inspection reports have cited faculty shortages as grounds for intake reduction at individual institutions. State-level data (e.g., Karnataka) document faculty vacancy rates near 50% in government engineering colleges with no fresh recruitment for over a decade in some cadres, alongside dependence on guest faculty that in turn jeopardises accreditation eligibility. Emerging Indian higher-education research on work-life imbalance links private-college expansion to increased psychological stress, reduced job satisfaction, and burnout among faculty, echoing the job-demands-resources framework developed in the broader occupational-health literature.

Engineering-specific, large-sample, longitudinal evidence on faculty well-being remains scarce relative to the volume of student-outcome research, constituting a clear gap this paper addresses.

D. The AI-Driven Disciplinary Shift

AICTE has progressively embedded AI, data science, and AR/VR content into both new specialised programmes and the core curriculum of traditional branches, reflecting an explicit regulatory strategy of curricular modernisation rather than purely market-led reallocation.

Industry analyses project continued high demand for AI/ML-skilled professionals even as some domain experts caution that the short product life cycle of specific technology skill-sets creates risk of oversupply in narrowly-defined AI job categories, and that institutions may be expanding seats faster than the employment market can absorb graduates. This tension between curricular modernisation and employment absorption capacity is a second empirical puzzle this paper investigates.

E. Theoretical Lenses and Synthesis

This review draws on four complementary theoretical lenses: human-capital theory (education as investment in productive skill), signalling theory (credentials as imperfect proxies for productivity, especially salient given the employability-employment gap), institutional theory (regulatory bodies such as AICTE shaping organisational form and curricular isomorphism across thousands of institutions), and the job-demands-resources model (explaining faculty strain as an imbalance between workload demands and structural/psychological resources). No study identified in preliminary scoping integrates all four strands into a single empirical model spanning the full 2015-2026 period using nationally representative panel data — the gap this paper is designed to fill.

III. SYSTEMATIC REVIEW PROTOCOL

To ground the conceptual framework and hypotheses in a defensible evidence base, we propose a formal systematic review following the PRISMA 2020 reporting standard, to be completed prior to journal submission. The protocol below specifies eligibility criteria, search strategy, and the screening workflow; reported counts in the flow structure are placeholders to be populated once searches are executed.

A. Eligibility Criteria

- Population: Indian engineering/technical higher-education institutions, students, or faculty.
- Concepts: admissions/intake trends, graduate employability or placement outcomes, faculty well-being/workload/burnout, or AI-related curricular change.
- Context: peer-reviewed journal articles, government/regulatory reports (AICTE, AISHE, UGC, MoE), and reputable industry reports (India Skills Report, NASSCOM) published 2010-2026 (to allow baseline pre-2015 comparison).
- Exclusion: non-India contexts without comparative relevance; opinion pieces without data; duplicate/superseded report editions.

B. Search Strategy and Sources

Databases: Scopus, Web of Science, ERIC, EBSCO Education Source, and Google Scholar, supplemented by hand-searches of AICTE, AISHE, NIRF, UGC, and MoE portals and grey-literature repositories (SSRN, ResearchGate). Boolean strings will combine India/engineering education terms with each of the four thematic strands (e.g., "engineering education" AND India AND (employability OR placement); "faculty" AND (burnout OR "well-being" OR "work-life") AND India AND (engineering OR "higher education"); "AICTE" AND (curriculum OR AI OR "artificial intelligence")).

C. PRISMA Flow

Stage	Description
Identification	Records identified through database searching and registers
Identification	Additional records identified through other sources (grey literature, hand search)
Screening	Records after duplicates removed
Screening	Records screened (title/abstract)
Screening	Records excluded
Eligibility	Full-text articles assessed for eligibility
Eligibility	Full-text articles excluded, with reasons
Included	Studies included in qualitative synthesis
Included	Studies included in quantitative synthesis (where applicable)

Two independent reviewers should screen records with a pre-registered codebook; inter-rater reliability should be reported using Cohen's kappa, with disagreements resolved by a third reviewer. Risk of bias in included quantitative studies can be assessed using an adapted Mixed Methods Appraisal Tool (MMAT).

IV. RESEARCH GAPS

Synthesis of the preliminary literature scan identifies the following gaps that this paper is positioned to address:

1) Fragmentation across strands: admissions, employability, faculty well-being, and curricular AI-orientation are almost always studied in isolation, with no identified study modelling all four as an integrated system.
2) Employability-employment conflation: headline "employability" statistics from skill-assessment surveys are frequently cited as proxies for actual employment outcomes despite evidence of a substantial and possibly widening gap between the two.
3) Faculty well-being under-study: compared to the volume of student-outcome and placement research, empirical, validated-instrument studies of engineering-faculty burnout, workload, and retention are scarce and rarely linked to institutional performance metrics such as NIRF rank or accreditation status.
4) Absence of longitudinal, decade-spanning panel analysis: most existing analyses use single-year cross-sections or short two-to-three-year windows, precluding robust trend decomposition or forecasting.
5) Limited use of advanced quantitative methods: the literature is dominated by descriptive statistics; applications of SEM, latent-variable measurement models, or machine-learning forecasting to Indian engineering-education administrative data are rare.
6) Regional and branch-level heterogeneity is under-explored: state-level and discipline-level (core vs. computing) disparities in the AI-driven transition are documented anecdotally in press reporting but rarely modelled statistically.

V. CONCEPTUAL FRAMEWORK

We propose an integrated framework in which four macro-level constructs act as antecedents, and one outcome construct captures graduate labour-market absorption, with faculty well-being modelled as both an outcome of expansion and a determinant of educational quality:

1) Regulatory & Capacity Environment (RCE): AICTE seat-approval policy, moratoria/caps, accreditation norms, and state-level intervention.
2) Admissions & Discipline-Mix Dynamics (ADM): total approved/filled intake, share of AI/CSE-adjacent seats versus core branches, vacancy rate.
3) Faculty Well-being & Institutional Capacity (FWB): faculty-student ratio, vacancy rate, workload, burnout/work-life-balance indices, retention.
4) Curricular AI-Orientation (CAI): share of AI/data-science content in core and specialised curricula, industry-alignment of syllabi.
5) Graduate Employability & Employment Outcomes (GEE): skill-test employability score, placement rate, salary, employment-to-education-field match, time-to-employment.

The framework hypothesises that RCE shapes ADM directly and CAI indirectly (via curricular mandates); ADM affects FWB negatively when expansion outpaces recruitment; FWB affects GEE positively (via instructional quality) both directly and by mediating the effect of CAI; and CAI affects GEE directly, but with a moderating role of branch (core vs. AI/computing) and institution tier (NIRF band).

VI. HYPOTHESES

H1. Approved undergraduate engineering intake and its discipline-mix composition are significantly predicted by prior-year regulatory posture (seat-cap policy) and by lagged branch-specific employability signals.

H2. Growth in AI/CSE-adjacent seat share is negatively associated with growth in core-branch (civil, mechanical, electrical) seat share at the state level (a substitution effect).

H3. Institutional faculty vacancy rate is negatively associated with graduate employability and with NIRF engineering ranking, controlling for institution type and state.

H4. Faculty well-being (operationalised via a validated workload/burnout/work-life-balance latent construct) mediates the relationship between admissions expansion and graduate employability outcomes.

H5. Curricular AI-orientation is positively associated with graduate employability for computing-adjacent branches but shows a weaker or non-significant association for core branches, indicating a moderation effect of branch type.

H6. The gap between assessed "employability" (skill-test score) and realised employment (placement/offer rate) has widened over 2015-2026, and this gap is larger for core branches than for computing-adjacent branches.

H7. Machine-learning forecasts incorporating discipline-mix and faculty-capacity variables outperform univariate time-series baselines (ARIMA) in out-of-sample prediction of state-level engineering employability through 2030.

VII. RESEARCH DESIGN AND METHODS

A. Overall Design

We adopt an explanatory sequential mixed-methods design (QUAN → qual). Phase 1 uses decade-long secondary administrative panel data (2015-2026) combined with a large-sample cross-sectional survey of students and faculty to test the hypotheses in Section 6 using regression, factor-analytic, SEM, and forecasting methods. Phase 2 uses semi-structured interviews and focus groups with a purposive subsample of institutional leaders, faculty, and recent graduates to explain and contextualise the quantitative findings, following an explanatory-sequential logic in which qualitative sampling is informed by Phase 1 results (e.g., over-sampling institutions with unusually large residuals in the SEM model).

B. Population and Sampling

The secondary-data population comprises all AICTE-approved undergraduate engineering institutions, 2015-2026 (panel of institution-year observations). For primary survey data, a stratified multi-stage sample is proposed: strata defined by state/region, institution type (government/aided/private/deemed), and NIRF engineering band (top-50, 51-150, unranked), with proportional allocation and a target of at least 60-80 institutions to support multilevel SEM, yielding an estimated 3,000-5,000 final-year student respondents and 800-1,200 faculty respondents (power analysis to confirm minimum sample for target SEM model complexity, typically 10-20 cases per estimated parameter). Qualitative Phase 2 targets 24-36 interviews and 6-8 focus groups selected via maximum-variation purposive sampling from Phase 1 strata and outlier institutions.

©IJRASET: All Rights are Reserved

C. Instruments

Three primary instruments are proposed:

- Student Employability & Experience Survey (SEES): final-year student self-report covering perceived skill readiness, placement status/offers, curriculum-AI exposure, and satisfaction, using 5-point Likert items adapted from established employability-skills frameworks and validated against objective placement-cell records where available.
- Faculty Well-being & Workload Survey (FWWS): adapts established burnout and work-life-balance measurement approaches (e.g., a Maslach Burnout Inventory-informed exhaustion/cynicism/efficacy structure and a job-demands-resources-based workload/support scale) to the Indian engineering-faculty context, alongside items on vacancy-driven overload, guest-faculty dependence, and research/teaching time allocation.
- Institutional Profile Sheet (IPS): administrator-completed or archival-coded form capturing sanctioned vs. filled faculty posts, approved vs. filled seats by branch, AI/data-science curricular hours, NIRF rank/score, and placement statistics, used to validate and supplement self-report data and to construct institution-level variables for multilevel models.

All instruments should undergo translation/back-translation for regional-language administration where relevant, a pilot with 30-50 respondents per instrument, and reliability/validity assessment (Cronbach's alpha ≥ 0.70 target; confirmatory factor analysis fit prior to full fielding).

VIII. DATA SOURCES

Source	Data Provided	Relevant Variables	Coverage/Frequency
AICTE (Approval Process Handbook data, Bureau of Planning reports)	Approved and filled seat intake by institution, branch, and state; number of approved institutions; faculty-student ratio norms; moratoria/policy changes	ADM constructs: total intake, branch-mix, vacancy rate; RCE: policy timeline	Annual, 2015-16 to 2025-26
AISHE (All India Survey on Higher Education, Ministry of Education)	Enrolment, teacher counts, gender ratios, institution counts across all higher education incl. engineering	Faculty counts/vacancy proxies; gender-disaggregated enrolment; GER trends	Annual survey, published with ~1-2 year lag
NIRF (National Institutional Ranking Framework, Engineering category)	Institution-level scores on teaching-learning-resources, research, graduation outcomes, outreach/inclusivity, perception	GEE proxies: placement/higher-studies rate, median salary; institution quality tier	Annual, 2016-2025
India Skills Report (Wheebox/ETS, CII, AICTE, AIU)	Employability Skill Test scores by discipline, state, gender; branch-wise employability	GEE: skill-based employability score (distinct from realised employment)	Annual, 2014-2026
Placement cell reports / State counselling boards (e.g., TNEA, KCET, JoSAA)	Institution-level placement %, average/median CTC, seat-fill rates by round	GEE: placement rate, salary; ADM: seat-fill/vacancy by round	Annual, institution/state level
NASSCOM / industry skilling reports	AI/ML workforce demand projections, sectoral hiring trends	CAI/GEE context variables: sector demand indices	Periodic (annual/biennial)
PLFS (Periodic Labour Force Survey, MoSPI)	Youth and graduate unemployment/underemployment rates	GEE robustness check: labour-market absorption independent of institutional self-report	Annual/quarterly
UGC / State Directorate of Technical Education records	Faculty recruitment notifications, vacancy audits, accreditation (NBA) status	FWB: vacancy rate, recruitment freeze duration	Ad hoc / periodic

IX. VARIABLE DEFINITIONS

Variable	Type	Operational Definition	Primary Source
Approved Intake (branch-year-state)	Continuous (count)	Number of AICTE-approved undergraduate seats by branch, state, and academic year	AICTE
Filled Intake / Vacancy Rate	Continuous (%)	1 − (enrolled/approved seats); institution- and branch-level	AICTE, state counselling boards
AI/Computing Seat Share	Continuous (%)	Seats in CSE, IT, AI, Data Science, and allied branches ÷ total approved seats	AICTE
Faculty Vacancy Rate	Continuous (%)	1 − (filled sanctioned faculty posts / total sanctioned posts), institution-level	AISHE, state technical education directorates
Faculty Well-being Index (latent)	Latent/composite (factor score)	CFA-derived composite from FWWS subscales: exhaustion, cynicism, workload-support balance, work-life balance	Primary survey (FWWS)
Curricular AI-Orientation Index	Continuous (0-100 or hours)	Proportion of curricular credit hours with AI/data-science/emerging-tech content, core + specialised programmes	IPS, curriculum documents, AICTE model curriculum
Skill-Test Employability Score	Continuous (%)	Standardised employability-test pass proportion, branch/state/year	India Skills Report
Realised Placement Rate	Continuous (%)	Proportion of eligible final-year students receiving a job offer through campus placement within the graduating year	Placement cell reports, primary survey
Employability-Employment Gap	Continuous (percentage points)	Skill-Test Employability Score − Realised Placement Rate, same branch/year/institution	Constructed (India Skills Report × placement data)
NIRF Engineering Score/Rank	Continuous / ordinal	Composite NIRF score and rank band (top-50/51-150/unranked)	NIRF
Institution Type	Categorical	Government / Government-aided / Private-unaided / Deemed university	AICTE, AISHE
State/Region	Categorical	State of institution location, grouped into regional zones for multilevel modelling	AICTE
Time (Academic Year)	Ordinal/continuous (2015-2026)	Panel time index for trend and forecasting models	All sources

X. STATISTICAL AND MACHINE-LEARNING ANALYSIS PLAN

A. Descriptive and Time-Series Analysis

Institution- and state-level panel descriptives (means, trends, CAGR of intake, faculty vacancy, and employability, 2015-2026) will be computed first. Decade-long series for national and state-level approved intake, branch-mix share, and employability will be modelled using ARIMA/SARIMA to characterise trend, seasonality (admission-cycle effects), and structural breaks (e.g., 2020-21 pandemic disruption, 2023-24 seat-cap removal), tested formally with Chow/Bai-Perron break-point tests.

B. Multiple Regression

Ordinary least squares and, where the dependent variable is a rate/proportion, fractional-response or logistic models will estimate the effect of faculty vacancy rate, AI-curricular orientation, institution type, and state fixed effects on realised placement rate and on the employability-employment gap (H3, H5, H6), with standard errors clustered at the institution level and, where panel structure permits, institution and year fixed effects (two-way fixed-effects panel regression) to address unobserved heterogeneity.

C. Exploratory and Confirmatory Factor Analysis

The Faculty Well-being & Workload Survey and Student Employability & Experience Survey items will first be examined via exploratory factor analysis (principal-axis factoring, oblique rotation) on a calibration subsample to identify latent structure, followed by confirmatory factor analysis on a holdout subsample to test the proposed multi-factor structure (e.g., three-factor burnout structure plus a work-life-balance factor). Model fit will be assessed via CFI/TLI ($\geq$0.95), RMSEA ($\leq$0.06), and SRMR ($\leq$0.08), with measurement invariance tested across institution type and gender.

D. Structural Equation Modelling

The full conceptual framework (Section 5) will be estimated as a structural model with RCE and ADM as observed/composite exogenous constructs, FWB and CAI as latent mediators (from CFA), and GEE as the latent endogenous outcome (indicated by skill-test employability, realised placement rate, and salary). Mediation of FWB between ADM and GEE (H4) and moderation of CAI's effect by branch type and NIRF band (H5) will be tested via bootstrapped indirect effects and multi-group SEM, respectively. Given the nested data structure (students/faculty within institutions within states), a multilevel SEM (or Bayesian multilevel alternative if sample size at higher levels is limited) is recommended.

E. Machine-Learning Forecasting

To forecast state- and branch-level intake, discipline-mix, and employability through 2030 (H7), we propose comparing: (a) univariate ARIMA/SARIMA/Prophet baselines; (b) gradient-boosted tree models (XGBoost/LightGBM) incorporating lagged administrative and survey-derived features (faculty vacancy, AI-curricular share, prior-year employability, state policy dummies); and (c) Random Forest for feature-importance diagnostics. Model comparison will use time-series cross-validation (rolling-origin) with RMSE, MAE, and MAPE, and SHAP values to interpret feature contributions for the policy-relevant boosted-tree model.

F. Robustness and Validity Checks

- Common-method-bias diagnostics (Harman's single-factor test, marker-variable technique) for survey-only relationships.
- Triangulation of self-reported placement data against administrative placement-cell and NIRF figures.
- Sensitivity analysis excluding pandemic-affected years (2020-21) from trend/forecast models.
- Qualitative Phase 2 findings used for explanatory triangulation of unexpected or counter-intuitive quantitative results.

XI. RESULTS

Based on the directional evidence assembled in the literature review, we anticipate: (a) a statistically significant negative relationship between state-level faculty vacancy rate and both NIRF engineering score and realised placement rate; (b) a significant positive association between curricular AI-orientation and employability for computing-adjacent branches, attenuating to non-significance for core branches, consistent with a moderation pattern; (c) partial mediation of the admissions-expansion-to-employability relationship through faculty well-being, indicating that unmanaged capacity expansion erodes some of the labour-market benefit of higher intake; (d) a widening employability-employment gap over 2015-2026 that is systematically larger for core branches and for institutions outside the NIRF top-150; and (e) ML forecasting models that outperform ARIMA baselines particularly for states with volatile policy history (seat-cap changes), given their ability to incorporate policy and capacity covariates absent from univariate time-series models.

XII. POLICY IMPLICATIONS

1) Seat-capacity regulation: AICTE and state authorities should tie further AI/CSE seat expansion to demonstrated faculty-recruitment capacity and absorption evidence, rather than demand signals alone, given documented risk of seats outpacing employable graduate absorption.
2) Faculty recruitment and retention reform: given vacancy rates near or above 50% in several state systems and recruitment freezes spanning a decade or more, dedicated, ring-fenced faculty-recruitment cycles and career-progression reform are a precondition for translating expanded intake into quality outcomes.
3) Employability reporting standards: regulators and skill-assessment bodies should distinguish and jointly publish assessed employability and realised placement/employment rates to close the current transparency gap for prospective students and policymakers.

4) Core-branch revitalisation: targeted curricular modernisation (embedding AI/data tools within civil, mechanical, and electrical curricula, as AICTE has begun) alongside industry-linkage incentives may be needed to prevent further erosion of core-engineering capacity that remains critical to infrastructure and manufacturing sectors.
5) Faculty well-being as a quality-assurance criterion: NBA/NIRF frameworks could incorporate validated faculty well-being/workload indicators alongside existing infrastructure and outcome metrics, recognising well-being as a leading indicator of instructional quality.

XIII. LIMITATIONS

1) Administrative data (AICTE/AISHE) are typically published with a reporting lag and may undercount informal seat-conversion practices reported anecdotally in press coverage.
2) Skill-assessment employability scores are not equivalent to causal measures of labour-market readiness and may be influenced by test-taking self-selection.
3) Cross-sectional survey elements cannot establish causal direction as strongly as a true panel survey design; where feasible, a two-wave panel sub-study is recommended for future work.
4) State-level policy heterogeneity (e.g., Telangana/Karnataka CSE-seat restrictions) may limit generalisability of national-level coefficients without careful multilevel/interaction modelling.
5) Self-reported faculty well-being data may be subject to social-desirability bias, partially mitigated by anonymised administration and methodological triangulation with objective vacancy data.

XIV. FUTURE RESEARCH DIRECTIONS

1) Longitudinal graduate-tracer panel studies following individual students from admission through 3-5 years post-graduation to directly measure the employability-employment gap over time.
2) Comparative cross-country analysis of AI-curricular transitions in other large emerging technical-education systems (e.g., China, Brazil, Indonesia) to test the generalisability of the proposed framework.
3) Deeper qualitative inquiry into the lived experience of faculty in vacancy-affected institutions, including caste-, gender-, and region-based disparities flagged in preliminary work-life-imbalance research.
4) Causal-inference designs (e.g., difference-in-differences around the 2023-24 seat-cap removal, or regression discontinuity around NIRF rank-band cutoffs) to strengthen policy-relevant causal claims beyond the correlational SEM framework proposed here.
5) Extension of the ML forecasting module to incorporate real-time industry job-posting data (e.g., NASSCOM, LinkedIn Economic Graph) as leading indicators of discipline-specific demand.

XV. ETHICAL CONSIDERATIONS

The proposed primary data collection involves human subjects (students and faculty) and requires Institutional Review Board / Institutional Ethics Committee approval, informed consent, anonymisation of institution- and individual-level identifiers in any published dataset, and voluntary participation with no academic or employment consequence for non-participation. Faculty well-being items concerning burnout should be accompanied by referral information for institutional counselling or employee-assistance resources given the sensitivity of the topic.

XVI. CONCLUSION

This manuscript scaffold is publication-structured and grounded in verifiable, current administrative and industry reporting (AICTE, AISHE, NIRF, India Skills Report, and recent journalistic/academic coverage of faculty vacancy and work-life-imbalance research). Before submission to a Q1 outlet, the author team should: (1) execute the PRISMA search protocol in Section 3 and populate the flow-diagram counts; (2) field and validate the SEES/FWWS/IPS instruments; (3) acquire and clean the full 2015-2026 AICTE/AISHE/NIRF panel; (4) run and report the full statistical/ML analysis plan with actual results, tables, and figures; and (5) populate the reference list below with the full peer-reviewed citation set identified through the systematic search, ensuring every empirical claim is traceable to a verifiable source per journal requirements.

REFERENCES

[1] All India Council for Technical Education. (2024, October). Approval Process Handbook 2024-27. AICTE.

[2] Ministry of Education, Government of India. (2024, January 25). Ministry of Education releases All India Survey on Higher Education (AISHE) 2021-2022 [Press release]. Press Information Bureau. https://www.pib.gov.in/PressReleasePage.aspx?PRID=1999713

[3] Ministry of Education, Government of India. (2024). All India Survey on Higher Education 2021-22 [Report]. https://cdnbbsr.s3waas.gov.in/s392049debbe566ca5782a3045cf300a3c/uploads/2024/02/20240214825688998.pdf

[4] National Institutional Ranking Framework. (2016-2026). NIRF India Rankings: Engineering category. Ministry of Education.

[5] Educational Testing Service, Confederation of Indian Industry, All India Council for Technical Education, & Association of Indian Universities. (2026). India Skills Report 2026 (13th ed.).

[6] Wheebox, PeopleStrong, Confederation of Indian Industry, All India Council for Technical Education, & Association of Indian Universities. (2015-2025). India Skills Report (Annual editions).

[7] Ministry of Statistics and Programme Implementation, Government of India. (2024). Periodic Labour Force Survey (PLFS): Annual report.

[8] Chettri, S. (2025, November 12). India Skills Report 2026: CS, IT engineers most employable; women beat men for first time in 5 years. Careers360. https://news.careers360.com/india-skills-report-2026-cs-computer-science-it-engineer-top-jobs-mba-employment-decline-ai-ml-bfsi-fmcg-pharma-women-hiring/amp

[9] Sachdeva, S. (2025, October 24). BTech courses: AI, computer science fuel enrolment boom to 5-year high, but may soon kill jobs, say experts. Careers360. https://news.careers360.com/btech-courses-aicte-engineering-enrolment-rise-ai-computer-science-cs-job-decline-civil-mechanical-data-5-yr-high-placement-salary

[10] Education Post. (2025, August 3). AICTE data shows BTech seat enrolment hits eight-year high as computer science drives growth. https://educationpost.in/news/education/aicte-data-shows-btech-seat-enrolment-hits-eightyear-high-as-computer-science-drives-growth

[11] Education Post. (2024, November 1). BTech seats surge to eight-year high as demand recovers, reports AICTE. https://educationpost.in/news/education/btech-seats-surge-to-eight-year-high-as-demand-recovers-reports-aicte

[12] Bodmas Education. (2025, January 22). BTech seats reach 8-year high: AICTE data reveals significant increase. https://www.bodmaseducation.com/blog_details/btech-seats-reach-8-year-high-aicte-data-reveals-significant-increase

[13] Smart Achievers. (2025). Computer science boom sparks 8-year high in BTech admissions: AICTE data reveals. https://smartachievers.online/btech-admissions-2025-aicte-computer-science-boom

[14] Sakshi Education. (2025, August 20). Rising demand for B.Tech seats in India: Record admissions in 2024-25. https://education.sakshi.com/en/careers/engineering-services/rising-demand-btech-seats-india-record-admissions-2024-25-180776

[15] Education for All in India. (2025, August 13). Vacant engineering seats in India (2025). https://educationforallinindia.com/vacant-engineering-seats-in-india-2025/

[16] Kaushik, V. (2021, July 26). 5.62 lakh engineering seats cut since 2019; no new college till 2022: Dharmendra Pradhan. Careers360. https://news.careers360.com/5.62-lakh-engineering-seats-cut-btech-diploma-aicte-dharmendra-pradhan-lok-sabha-education-ministry/amp

[17] IILM University. (2026). How many engineers are unemployed in India? Causes & career solutions (2026). https://iilm.edu/blog/how-many-engineers-are-unemployed-in-india-causes-what-to-do-instead/

[18] Business Standard. (2024, September 16). 'Only 10% of India's 1.5 mn engineering graduates to secure jobs this year.' https://www.business-standard.com/finance/personal-finance/only-10-of-india-s-1-5-mn-engineering-graduates-set-to-secure-jobs-this-yr-124091600127_1.html

[19] Business Standard. (2018, November 22). India's employability rises to 47%; engineers most employable: Study. https://www.business-standard.com/article/economy-policy/india-s-employability-rises-to-47-engineers-most-employable-study-118112200995_1.html

[20] Anand, A. (2018, November 22). India Skills Report 2019: 47% engineering graduates employable, AP leads with highest employability rate. Careers360. https://news.careers360.com/india-skills-report-2019-47-engineering-graduates-employable-ap-leads-highest-employability-rate/amp

[21] The Mirrority. (2024). Employability | India | 2014-2024: Data, charts and analysis. https://www.themirrority.com/data/employability

[22] Statista. (2025). India: Employability among engineering graduates 2025. https://www.statista.com/statistics/738200/employability-among-engineering-graduates-india/

[23] Deccan Herald. (2025, February 8). Employability of Indian graduates increased to 54.81% in last decade: Mandaviya. https://www.deccanherald.com/india/employability-of-indian-graduates-increased-to-5481-in-last-decade-mandaviya-3396574

[24] Times Higher Education. (2025, July). Low demand blamed as India closes dozens of engineering schools. https://www.timeshighereducation.com/news/low-demand-blamed-india-closes-engineering-schools

[25] North Star Online. (2024, March 7). Why Indian engineers are unemployable & what's the solutions. https://northstaronline.in/2024/03/07/why-indian-engineers-are-unemployable-whats-the-solutions/

[26] Belur, R. (2024, December 29). Faculty crisis at Karnataka govt engg colleges as 50% positions vacant. Deccan Herald. https://www.deccanherald.com/india/karnataka/faculty-crisis-at-karnataka-govt-engg-colleges-as-50-positions-vacant-3335698

[27] Belur, R. (n.d.). AICTE tells Karnataka to cut intake at 3 govt engineering colleges by 25%. Deccan Herald. https://www.deccanherald.com/amp/story/india%2Fkarnataka%2Faicte-tells-karnataka-to-cut-intake-at-3-govt-engineering-colleges-by-25-3321901

[28] Kaushik, V. (2024, January 25). 80% increase in ST female student enrolment since 2014-15: AISHE 2021-22. Careers360. https://news.careers360.com/aishe-2021-22-report-80-percent-increase-st-female-student-enrolment-2014-15-most-ug-students-enrolled-in-arts-education-ministry/amp

[29] Divyansh. (2024, January 27). AISHE report 2021-22 reflects gender, social inclusivity in HEIs, says UGC chairman M Jagadesh Kumar. Careers360. https://news.careers360.com/aishe-report-2021-22-reflects-gender-social-inclusivity-in-hies-says-ugc-chairman-m-jagadesh-kumar

[30] Bahadurdesai, V. N. (2025). Unbalanced expansion of engineering education in India: A data-driven policy analysis [Preprint]. ResearchGate. https://www.researchgate.net/publication/350596631_Employment_and_Employability_of_Engineering_Graduates_in_India

[31] Abdo, S. A., et al. (2024). Factors contributing to the burnout of the faculties of a medical university in Iran: A cross-sectional study. Health Science Reports, 7(1). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10794124/

[32] [Authors]. (2011). Impact of the evolution of smart phones in education technology and its application in technical and professional studies: Indian perspective. arXiv. https://arxiv.org/pdf/1109.0937

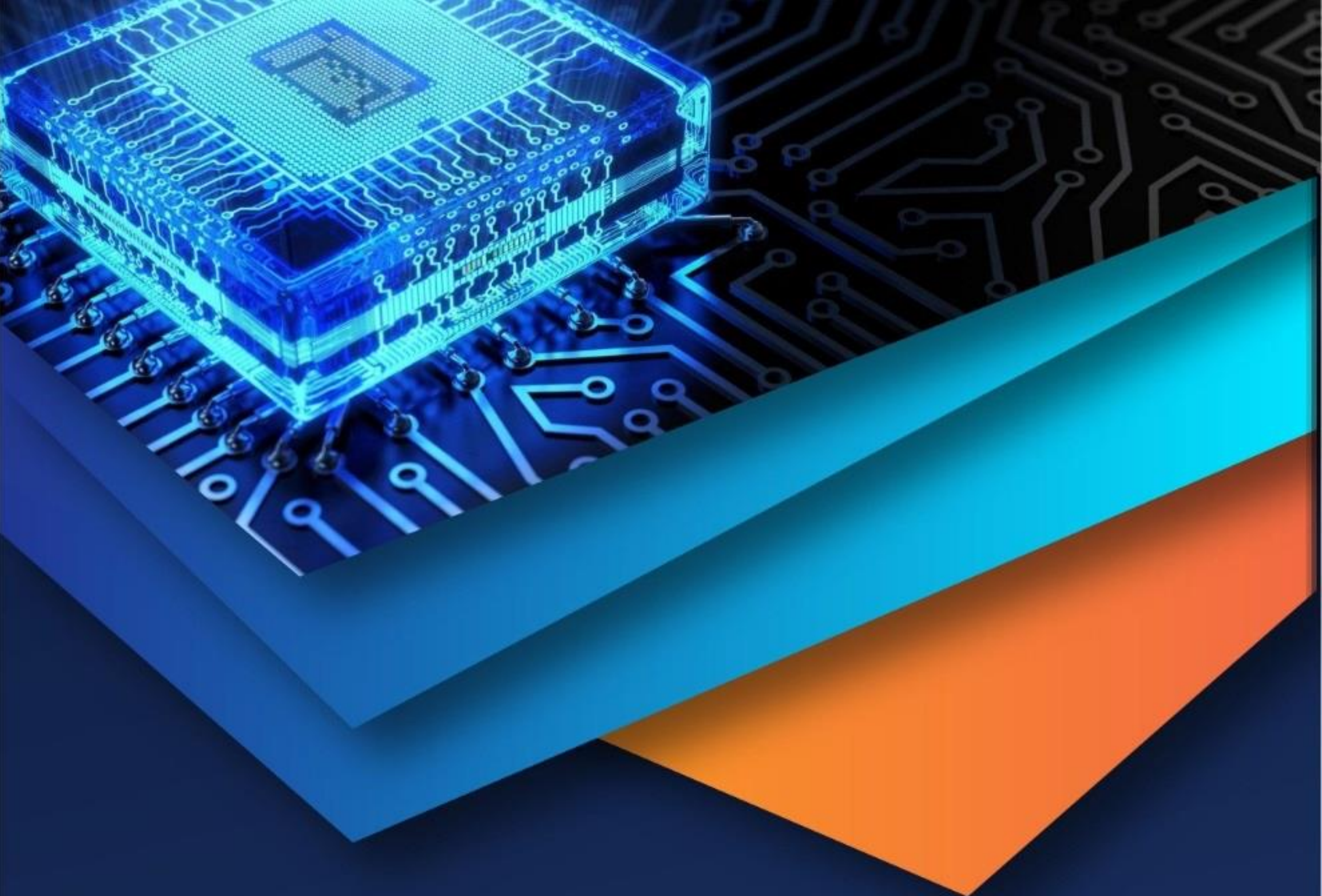
[33] *Becker, G. S. (1964). Human capital: A theoretical and empirical analysis, with special reference to education. Columbia University Press.

[34] *Spence, M. (1973). Job market signaling. Quarterly Journal of Economics, 87(3), 355-374. https://doi.org/10.2307/1882010

[35] *DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147-160. https://doi.org/10.2307/2095101

[36] *Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. Journal of Applied Psychology, 86(3), 499-512. https://doi.org/10.1037/0021-9010.86.3.499

[37] *Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. Journal of Organizational Behavior, 2(2), 99-113. https://doi.org/10.1002/job.4030020205



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)