Institutional Quality in AI the Era: IQAC Opportunities and Challenges in Adopting Analytical Tools for improvements

Dr. Irfan Ahmad Khan

Postdoctoral Researcher, Lincoln University College

Irfan16143@gmail.com

Abstract:

The emergence of quality assurance (QA) in higher education through the use of artificial intelligence (AI) analytical tools is a challenging, but transformative phenomenon. Yet, as much as there is the sense of urgency, the IQACs are also being burdened with the responsibility in not only tapping into these transformative analytic synergies, but also with a range of requirements which are couched in organizational, technical as well as ethical terms. This paper discusses the opportunities and challenges faced by IQACs in Indian institutions of higher learning in enhancing AI analytical tools to ensure continuous quality improvement. The study is a convergent parallel mixed-methods design based on 50 IQAC coordinators and quantitative survey data and 10 in-depth interviews and six institutional case study as a source of qualitative input. Data collection instrument: A validated 20-item structured questionnaire relying on the Technology Acceptance Model (TAM), semi-structured interview guides, field notes of observations and review of documents. Synthesis is done with thematic analysis, statistical modelling and integration matrices. The preliminary findings indicate the variation in the level of AI tool adoption in various kinds of institutions, where perceived usefulness and digital readiness have been established as the determinants. The findings give a contextualized perspective of AISQ in limited resource-based academic settings.

Keywords: Institutional quality assurance, Artificial Intelligence Analysis. IQAC, Technology Adoption, Mixed-Method Research

1. Introduction:

The digital technologies that have transformed higher education globally have put the mechanisms of institutional quality assurance in the spotlight like never before. One of the most notable changes is the increasing use of artificial intelligence (AI) analytical tools in institutional governance, monitoring, and the process of improvement. The transition of the paper-based quality monitoring practice to data-driven and AI-assisted decision-making systems is now a challenge to the Internal Quality Assurance Cells (IQACs) that are required institutions in Indian higher education to ensure continuous quality improvement.

Although the potential of AI to facilitate predictive analytics, real-time performance monitoring, and intelligent benchmarking is well-documented, the real implementation of these tools in IQACs is still not very consistent and cohesive. Among the multidimensional sources of adoption paths, institutional preparedness, administrative determination, digital infrastructure, faculty capability, and regulatory adherence can be noted. The lack of alignment between AI promise and its real use in quality assurance frameworks is one of the key areas that need to be investigated empirically.

The present study will be driven by the necessity to produce context-sensitive evidence regarding the perceptions, adoption, and integration of AI analytical tools by IQAs into the quality improvement processes. The study lies at the crossroads of the quality management of higher education, theory of technology adoption, and organizational change. Through a stringent convergent parallel mixed-method structure, the proposed research will yield holistic, validated findings that can directly be translated into policy and practice, as well as future studies in the institutional quality assurance field.

This research will aim to achieve the following objectives:

- To map available AI analytical tools applied or contemplated to be applied by IQACs in Indian higher education.
- To determine the perception of IQAC coordinators towards the usefulness, ease of use, and readiness of adopting AI tools.
- To determine major opportunities and obstacles to the integration of AI in the quality assurance processes.
- To formulate recommendation on policy and practice based on contexts of AI-enabled institutional quality management.

2. Related Works

The research on the use of AI in quality assurance in higher education is still relatively young but quickly growing. Theoretical background in this field has been based on the Technology Acceptance Model (TAM) proposed by Davis [1], which assumes that perceived usefulness and perceived ease of use are the key factors that determine whether technology is adopted or not. Later extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. [2], have extended the explanatory area to social influence, facilitating conditions and institutional context.

Pedro et al. [3] conducted the general review of AI applications in education, recognizing predictive analytics, natural language processing, and intelligent tutoring systems as the prevalent paradigms. Baker and Inventado [4] pointed out the transformative nature of educational data mining in the institutional decision making. In quality assurance, in particular, Seeber et al. [5] considered the potential of data analytics in enhancing accreditation procedures, and Lim et al. [6] reported the difficulties related to algorithmic accountability and data governance in post-secondary education.

In the Indian setting Sharma and Mishra [7] examined digital preparedness in NAAC-approved institutions and found that there are serious discrepancies in infrastructure and human capital. Choudhury and Pattnaik [8] were interested in the policy aspects of IQAC digitalization, and it was necessary to build capacity and manage institutional change. Nevertheless, there is still a lack of empirical studies with mixed-method designs that can holistically describe both the quantitative adoption trends and the qualitative experiential aspects.

The table below gives a comparative synthesis of major related works, their methodologies, areas of focus and the gaps that the current study aims to fill.

Study	Focus Area	Methodology	Key Findings	Context	Gap Addressed
Davis (1989) [1]	Technology Acceptance	Quantitative Survey	TAM constructs predict adoption	General IT	No education-specific focus
Venkatesh et al. (2003) [2]	UTAUT Model	Empirical	Extended TAM with social influence	Workplace IT	Limited HE application
Pedro et al. (2019) [3]	AI in Education	Systematic Review	AI dominant in tutoring and analytics	Global HE	Limited quality assurance focus
Baker & Inventado (2014) [4]	Educational Data Mining	Review	EDM supports institutional decisions	USA	No IQAC-specific insights
Seeber et al. (2020) [5]	Analytics in QA	Case Study	Analytics enhances accreditation	European HE	No mixed-methods approach
Lim et al. (2021) [6]	AI Governance in HE	Qualitative	Data ethics challenges identified	Asian HE	No adoption framework offered
Sharma & Mishra (2022) [7]	Digital Readiness	Survey	Infrastructure gaps in India	Indian HE	Qualitative insights missing
Choudhury & Pattnaik (2023) [8]	IQAC Digitalisation	Policy Analysis	Need for capacity-building	Indian HE	Empirical evidence lacking
Present Study	AI in IQAC Quality Assurance	Mixed-Methods (Convergent Parallel)	Integrated adoption framework with contextual evidence	Indian HE (Multi-institutional)	Holistic empirical study with policy implications

Table 1: Comparative Analysis of Related Works

3. Key Contributions

The original contributions that this paper has to the literature are:

- Establishes and justifies mixed-methods research that is adapted to the IQAC setting by incorporating TAM constructs along with institutional preparedness indicators, which are unique to Indian higher education.
- Offers the first large-scale empirical study (n=50 quantitative; n=10 qualitative; n=6 case studies) about patterns of AI tools adoption within IQAC typologies, early adopters, mid-stage adopters, and non-adopters.
- Creates an Integration Matrix to provide the convergence and divergence between quantitative and qualitative results, providing a policy recommendation that is subtle in nature.
- Theorizes a contextual model of AI-supported quality assurance that can be applied to resource-restricted academic institutions that are subject to national accreditation and regulation systems.
- Adds methodological rigor with triangulated validation processes cross-level quality on quantitative, qualitative and integration levels.

4. Method

4.1 Research Design

The design of the current study is convergent parallel mixed-methods design where quantitative and qualitative data are gathered concurrently, analysed separately and synthesised during the interpretation phase. This is a design that is especially appropriate to explore the complex phenomena of adoption where numerical data is not sufficient to reflect the experience, organizational, and cultural aspects of technology integration. The mixed-methods strategy allows conducting a systematic triangulation, which increases internal validity and context richness of conclusions.

4.2 Sampling Strategy

In the quantitative strand, stratified random sampling was used to sample 50 IQAC coordinators in five geographic areas of India with institutional type stratification consisting of universities (50%), autonomous colleges (30%), and affiliated colleges (20%). In the qualitative strand, the purposive sampling technique was used to determine ten information rice respondents, three IQAC coordinators, two senior administrators and five faculty representatives who were chosen according to their stage of adoption of the AI tool. Also, six institutions were chosen on the basis of multi-case studies: two of them were early adopters with highly developed AI analytics application, two were middle adopters with incomplete application, and to was a non-adopter with old-fashioned quality assurance methods.

4.3. Ethical Considerations

The Institutional Review Board (IRB) gave ethical clearance in line with the university ethics policy of research and the UGC ethical guidelines. All participants were obtained written informed consent, with voluntary participation and penalty of withdrawal being explained clearly. The protection of institutional identities was achieved by means of pseudonymisation and aggregated reporting was used to avoid identification. All data were kept in encrypted, password-protected repositories that were only available to the core research team. There are no financial relationships between the researcher and AI analytics vendors, and the researcher was not institutionally affiliated with any of the participating sites, thus ensuring independence and transparency.

5. Experiments and Results

5.1. Quantitative Findings

Respondent survey results of 50 IQAC coordinators indicated a big difference in the use of AI tools among the types of institutions. The descriptive analysis showed that universities had the highest mean score of readiness to adopt ($M=3.82$, $SD=0.71$), then autonomous colleges ($M=3.21$, $SD=0.84$), and finally the affiliated colleges had the lowest readiness ($M=2.48$, $SD=0.93$). In general, 34 percent of the respondents have actively used at least one AI analytical tool in quality assurance processes and 42 percent had tried the tools without formal adoption and 24 percent had not engaged in AI-based analytics.

The TAM-based instrument was validated by factor analysis, the two main factors Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) accounted 61.4% of the overall variance. The structural equation modelling showed that PU was the most predictive of behavioural intention to adopt AI tools ($=0.67$, $p< 0.001$), and then institutional digital readiness ($=0.44$, $p < 0.01$). PEOU showed a great indirect influence through PU ($=0.39$, $p<0.01$).

5.2. Qualitative Findings

Thematic analysis of ten in-depth interviews lead to four over-theminges including: (1) Perceived Transformative Potential, (2) Structural and Infrastructural Barriers, (3) Capacity Gaps and Training Needs, and (4) Regulatory and Ethical Concerns, yield predictive performance information, and simplify accreditation reporting. Nevertheless, the theme of poor digital infrastructure, organisational change resistance, and data privacy and algorithmic transparency were strongly foregrounded.

5.3. Case Study Evidence

The cross-case analysis of the six institutional case studies has found that there are differentiated adoption trajectories. By the time the institutions became early adopters, they had invested in specialized data governance systems, had appointed AI champions at the top of IQAC, and had incorporated AI dashboards into the reporting processes at National Assessment and Accreditation Council (NAAC). Mid-stage adopters were selective, pilot-phase adopters due to budget constraints and faculty scepticism. Non-adopter institutions said that they were dependent on manual data collection and that they did not have an institutional leadership requirement as the main obstacle to AI integration.

5.4. Integration of Findings

The integration matrix showed good convergence between quantitative and qualitative data of centrality of institutional readiness and leadership commitment as determinants of AI adoption. It was found that there was divergence in the perception of data privacy risk, with quantitative scores showing moderate concern (M=3.14), and qualitative stories showing acute concern with data sovereignty and dependency on vendors. The limitation of Likert-based tools in measuring affective and contextual aspects of technology anxiety is highlighted by this divergence, which justifies the importance of mixed-methods approach.

6. Discussions

The results of this shed light on the complicated, non-linear route upon which IQACs interact with the AI analytical devices. The high predictive ability of Perceived Usefulness to adoption intention is in line with existing theory of TAM [1] but supersedes it in a significant way by showing that institutional readiness; i.e. digital infrastructure, leadership support, organisational culture etc. is equally important variable in higher education quality assurance context. This indicates that any intervention that focuses on improving the design of a tool as it faces the user will not be adequate without structural investment in institutional capacity.

Of particular interest is the difference in data privacy perceptions between the quantitative and qualitative strands. Likert scores might fail to capture the intensity of institutional anxiety about data ownership, especially in the situations where IQAC coordinators are not familiar with the frameworks of cloud-based analysis governance or where university legal infrastructure has not established sufficient data protection policies. This discovery demands that ethical AI governance be explicitly addressed as a precondition, not an ancillary issue, in adoption planning.

The observed adoption ladders among early adopters, mid-stage adopters, and non-adopters is a form of diffusion-of-innovation pattern as shown in the Rogers [9] framework, where institutional innovativeness, availability of resources and change leadership dictate where one falls along the adoption curve. Imperatively, the case studies show that early adopter institutions had an advantage not only because of financial capital but also because of the strategic placement of AI champions who facilitated the passage of technical knowhow and institutional quality culture - human facto often underestimated in technology adoption literature.

A regulatory environment of Indian higher education consisting of NAAC accreditation systems and UGC regulations presents distinct dynamics of adoption that do not fit into Western-focused models. The contexts that IQAC coordinators work in are rather compliance-intensive, where the perceived threat of implementing unvalidated AI tools in the processes related to accreditation impose institutional conservatism. Future versions of national quality models should thus include explicit standards of AI literacy and institutional sandboxes to experiment with.

Combined, these results would indicate that an effective application of AI in IQAC settings would have to be a multi-layered strategy: at the national policy level, a systemic approach would need to be established that would facilitate the investment in infrastructure, at the organisational level, AI governance structures would have to be established, and at the individual level, data literacy skills would need to be developed. This study suggests using an integrated framework that provides a systematic route through which institutions at different levels of adoption can plan to move strategically towards AI-enabled quality assurance.

7. Conclusions:

This study leads to the following pointwise conclusions:

1. **Problem Statement Addressed / Motivation.**

   The gap in the body of empirical evidence on how IQACs in Indian institutions of higher education view and implement AI analytical tools as a tool of continuous quality improvement is critical and has been filled by this study. Inspired by the growing gap between the transformative power of AI and the limited, uneven nature of its application in the institutional quality assurance systems, the study aimed to produce evidence-based knowledge that can be used across the broad institutional typologies.

2. **Method Used**

   The convergent parallel mixed-methods research design was used, which included a quantitative survey (n=50), qualitative in-depth interviews (n=10), and six institutional case studies. The data collection, based on the Technology Acceptance Model (TAM), was accompanied by the measures of institutional readiness. Structural equation modelling (SPSS/AMOS), thematic coding (NVivo), cross-case analysis, and a five-step data integration protocol with joint comparison tables, cross-validation and integration matrices were used to ensure analytical rigour.

3. **Key Findings**

   Among IQAC coordinators, perceived Usefulness and institutional institutional digital readiness are the best predictors of AI adoption intention. There exists a great stratification of adoption patterns by the type of institution, universities performing better than colleges. The qualitative analysis revealed four main themes, which included transformative potential, infrastructural barriers, capacity deficits and regulatory concerns. The evidence presented in case studies proved that early adopters are successful due to AI champion leadership and data governance systems rather than resources. The quantitative tools seriously underestimate data privacy anxiety and need to be amplified qualitatively.

4. **Limitations and Future Work.**

   The research has the following limitations. To begin with, the sample is purposely chosen and focused on five geographic regions of India making it difficult to generalise to other national or international higher education settings. Second, longitudinal dynamics of adoption are not modeled, since the cross-sectional design offers a one-point-in-time view of a changing phenomenon. Third, it uses self-reported survey data, which presents social desirability bias. Fourth, the case studies are limited by access and might not be representative of institutional variation at scale.

5. **Future research should pursue:**

   (1) longitudinal follow-ups of the AI adoption patterns in IQACs within three to five years; (2) cross-national comparative research studies on AI-enabled quality assurance in various regulatory settings; (3) the creation and validation of a standardised AI Readiness Index specifically adjusted to quality assurance organisations in higher education; and (4) experimental or quasi-experimental research studies that investigate intervention programmes.

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