Validating Institutional AI Tool Adoption: Real-World Barriers and Determinants

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Abstract

The present paper is the findings of Phase 3 of a mixed-method research on the adoption of AI tools by Internal Quality Assurance Cells (IQACs) in higher education institutions in India. Based on the outcomes of Phase 2 methodology, Phase 3 will focus on the actual data collection developments (50% done in 25 institutions) and confirmation of research hypotheses. Using the identical convergent parallel mixed-methods design of 50 IQAC coordinators in five regions of India, the study confirms four Phase 2 results: (1) Perceived Usefulness as the most important adoption determinant, (2) Digital Readiness as an essential enabling factor, (3) Institution Type Variation in adoption rates, and (4) Adoption as a progressive 18-month process. Three barriers emerge out of the real world data collection, which include inconsistency of data format between the regulatory bodies, low technical competency of personnel, and poor IT infrastructure. Regional analysis indicates that Gujarat (15 institutions) is the most progressive in the initiatives of adoption whereas Maharashtra (7 institutions) and others are lagging. Phase 2 quantitative predictions are confirmed by qualitative evidence, and systemic barriers that are beyond technological limitations are identified. Implications deal with IQAC leaders, policymakers and the higher education systems. This validation study offers empirical data that implementing AI tools effectively necessitates systemic change in data governance, investment in infrastructure, and capacity-building of staff, rather than technology itself.

Keywords: AI Tool Adoption, Data Governance, Digital Readiness, IQAC, Higher Education, Validation Study, Mixed-Methods Research

1. Introduction

This longitudinal research programme in the second phase developed a strict mixed methodology approach to the research on the adoption of AI tools in Internal Quality Assurance Cells (IQACs). The methodology produced four initial results that suggested perceived usefulness and digital readiness make the first dominating determinants of adoption, with institution type and stage of adoption, mediating these relationships. Phase 3 shifts are concerned with methodology validation to actual empirical validation in reality by active data gathering in 50 Indian higher education institutions.

The disjunctive nature of Phase 2 to Phase 3 begs some basic questions: Do the theoretical predictions of Phase 2 stand up in the face of institutional complexity at a real world scale? What are the unexpected impediments in real data collection? What is the interaction between regional contexts, types of institutions, and stages of adoption to facilitate or hinder the integration of AI tools?

The following proceeding answers these questions by analysing 50% completed data collection (25 institutions, 8 interviews, 3 case studies initiated) in five geographic areas across Gujarat, Maharashtra and other states in India. The research pinpoints three systemic obstacles, inconsistency in data format, lack of technical competence in staff and insufficient IT infrastructure, which confirm Phase 2 results and further the knowledge base of technology adoption theory to institutional change management and regulatory governance.

2. Phase 2 Recap: Research Foundation

Phase 2 research (presented at Conference 2) established a convergent parallel mixed-methods design with specific hypotheses grounded in Technology Acceptance Model (TAM) theory. The methodology included: (1) Survey of 50 IQAC coordinators across five regions using a 20-item validated instrument, (2) Ten in-depth interviews with information-rich respondents, (3) Six institutional case studies representing early adopters, mid-stage adopters, and non-adopters, and (4) Mixed analytical approaches combining structural equation modelling, thematic analysis, and,integration,matrices.

Phase 2 findings indicated: Finding 1 , Perceived Usefulness is the primary driver of AI tool adoption (early adopters: 78% perceive high usefulness; non-adopters: 45%); Finding 2 , Digital Readiness is a critical enabling factor (infrastructure-adoption correlation: r=0.82); Finding 3 , Institution Type Variation in adoption rates (Universities: 65%; Autonomous colleges: 48%; Affiliated colleges: 32%); Finding 4 , Adoption follows a gradual three-stage process spanning approximately 18 months (Awareness →Consideration → Adoption).

Phase 3 research systematically validates these Phase 2 findings against real-world data collection experience while identifying implementation barriers previously unmeasurable through Phase 2 methodology

3. Phase 3 Progress Status

Data collection for Phase 3 is currently 50% complete. Out of the target population of 50 IQAC coordinators, surveys have been completed by 25 institutions (50 percent), 8 out of 10 scheduled interviews are in progress and 3 out of 6 institutional case studies have been started. The regional distribution indicates that Gujarat has a higher number of completed institutions (15 out of 60 completed sample) followed by Maharashtra (7 institutions) and other regions (3 institutions). Response rates are high at 95 and the interview completion and the document collection is also at 80 and 85 respectively. On schedule to have full data collected in 6 months

(2 months beyond date of conference), and have full analysis done in months 7-8 and Phase 4 framework of the implementation planned in months 9-10.

4. Real-World Barriers Discovered During Data Collection

4.1 Data Format Inconsistency across Regulatory Bodies

The biggest challenge found across the 25 surveyed institutions is the need to keep data in several formats for various regulatory and accreditation needs. IQACs are supposed to report to NAAC (National Assessment & Accreditation Council) as Format A, NBA (National Board of Accreditation) as Format B, state level systems as Format C, university level systems as Format D and AI analytics platforms as Format E. This fragmentation puts a systemic burden on the IQAC coordinator consuming about 60% of his time for formatting data and only 40% of the quality improvement activities. Having to handle multiple data formats like five or more makes discovering and using new AI tools less beneficial in their eyes—more technology feels like more hassle in data management. It's all about 60 per cent of my time is spent on data formatting, not on improving quality. Why use AI tools when it's already difficult enough to handle the basics!"

4.2 Low Technical Competency of IQAC Staff

This is one of the secondary however, significant impediments is poor technical competence of entire staff of IQAC. IQAC coordinators have an average age of forty or more with mostly academic (teaching/ research) background and basic computer skills. Administrative employees are familiar with the basic processes of their jobs but not as much with technology. Faculty members involved in IQAC activity have no teaching centric approach and show reluctance of using technology. Training needs identified through data collection included 70%: basic IT competency; 85%: data management training; 90%: Guiding on reading and understanding the results of analytics; and 95%: hands-on training on AI tools. The lack of competency for working with the AI tool at an institutional level is a major challenge for implementation.

4.3 Inadequate IT Infrastructure

Study findings indicate that there is significant difference in the level of infrastructure from one category of institution to another. All of the Universities (15 surveyed) have modern IT facilities and IT infrastructure, and have good to excellent internet access and cloud storage facility with an IT support team. In infrastructures for autonomous colleges (7 surveyed), connectivity is not uniform as some are connected, some are partially connected, and others are completely disconnected, there is a moderate aging infrastructure with minimal use of cloud service and partial time IT support. There are very few IT support staff in affiliated colleges (3 surveyed) the infrastructure is basic and outdated with slow/unreliable internet, having minimal cloud storage. These specific gaps would consist of: Storage and processing constraints (inability to store or process large amounts of analytical data sets, or to do so effectively), connectivity constraints (slow connections in smaller towns and unreliable connections), hardware constraints (old computer equipment and servers with frequent breakdowns), and software constraints (no AI tools installed, limited data management systems, old operating systems used). Most colleges (small ones) don't have the budget to invest in infrastructure (~ ₹5 lakhs – 10 Lakhs) while larger institutions (autonomous colleges) have been limited to ~ ₹15 lakhs – 25 Lakhs and Universities have been limited to ₹50+ Lakhs.

5. Validation of Phase 2 Findings

5.1 Finding 1: Perceived Usefulness as Primary Determinant

It was concluded in Phase 2 that perceived usefulness is the most significant AI adoption motivator. This prediction is borne out by Phase 3 field data: institutions that have a high degree of difficulty with data format complexity have low perceived usefulness of AI tools. The result of the regional analysis reveals that the perceived usefulness of institutions is significantly higher in Gujarat (15 surveyed institutions with good data management systems) as compared to institutions in Maharashtra (7 surveyed institutions with moderate data management systems) and other regions (3 surveyed institutions with poor data management systems). Interview data shows that coordinators see the use of AI tools as an 'addition to already overwhelming data environment'. This confirms quantitative finding in Phase 2 that perceived usefulness (78% vs. 45% in early adopters and non-adopters respectively) directly influences the intention to adopt. Finding VALIDATED.

5.2 Finding 2: Digital Readiness as Critical Enabling Factor

Digital readiness (infrastructure + skills) was identified as one of the key moderating variables in Phase 2 with a correlation of r=0.82 to adoption. This is confirmed by the empirical evidence from Phase 3; the average time taken to implement AI tools is 3-6 months for universities with good infrastructure, 6-12 months for autonomous colleges with moderate infrastructure and has not been possible for affiliated colleges with weak infrastructure even if they will. The evidence from the case studies indicates that AI tool dashboard integration in Gujarat University is complete after 4 months, whereas implementation has been halted after 8 months at Maharashtra's autonomous college. One affiliated college quit its pilot project of an AI tool because of the limitation in infrastructure. The real world validation of this progression directly confirms Phase 2's quantitative prediction that infrastructure is not just useful, but crucial for successful adoption. Finding VALIDATED.

5.3 Finding 3: Institution Type Variation

The results of Phase 2 showed the variation in the rate of adoption in the universities, autonomous colleges, and affiliated colleges: 65% and 48% respectively, in universities and autonomous colleges, 32% in affiliated colleges. The quantitative result is explained by Phase 3 qualitative data which suggests that universities have better infrastructure, more technology competent faculty, dedicated IT support and resources to enable adoption. In some cases, readiness is mixed and resources not up to scratch in the case of autonomous colleges while leadership is cautious. Lack of adequate infrastructure, lack of skills and no IT support are structural limitations of affiliated colleges. In addition, interview analysis indicates that leadership motivation does not affect the adoption capacity, since it is directly dependent on the number of institutions. Smaller institutions desire to use AI tools, but don't have the structure in place. This confirms that the type of institution (captured by size and institutional resources) is a strong moderator of adoption as found in Phase 2. Finding VALIDATED.

5.4 Finding 4: Gradual Adoption Process

Phase 2, which had a predicted 18-months adoption process, saw three stages: Awareness (0-3 months), Consideration (3-12 months), Adoption (12-18+ months). In Phase 3 data collection, just this progression is revealed. The adoption trajectory is depicted by the Gujarat institutions — 3 in the adoption stage, 7 in consideration and 5 in the awareness stage. This means that the adoption rate is 0, consideration rate is 4 and the awareness rate is 3 at Maharashtra institutions, which is about 12 months behind Gujarat. Others regions are 0 for adoption, 1 for consideration and 2 for awareness. The evolution of AI adoption that's been anticipated for Phase 2 has been confirmed in this staged progression, which demonstrates that a quick and costless adoption of AI is not possible, but instead needs to follow a series of deliberate stages of evaluation and capacity development before institutions can reach full adoption. Why 18+ months? Coordinated effort over longer periods is needed to address infrastructure issues (3-6 months), for training staff (3-6 months), for pilot implementation (3-6 months), and to fine-tune systems (remaining period). Finding VALIDATED.

6. Discussion

Phase 3 validation study shows that the institutional adoption of AI tools is inherently limited not by the technology but by the systemic factors: a fragmented data governance, lack of human capital, and infrastructure shortage. This observation moves the explanatory emphasis of Technology Acceptance Model (TAM) constructs to the institutional change management and regulatory policy structures.

The finding that the discrepancy between data format in NAAC and NBA compared to state bodies and university-specific systems results in a 60%-40% time distribution issue (formatting versus improvement) is a direct cause of low perceived usefulness. When simple data infrastructure is still fractured, coordinators are rational in their opposition to embracing new AI tools. This implies that pre-requisite policy change that standardizes the data requirements in regulations is not an addition but a pre-requisite to AI adoption.

The technical capability gap (70-95% of personnel need training between IT literacy and AI operations) validates that scaling to enable technology adoption needs capacity-building. Without an appropriate investment in the staff development, policymakers and institutional leaders cannot anticipate successful implementation of AI.

The difference in infrastructure between the types of institutions demonstrates that the Indian system of higher education is bifurcated: universities that can promote AI innovation; colleges that structurally cannot introduce modern technologies. This inequality is an equity issue that needs to be addressed through policy.

A combination of these Phase 3 results indicates that successful AI-enabled quality assurance needs triple-level intervention: national policy reform to standardize data formats, institutional infrastructure investment, and capacity-building of individual staff. Technology adoption is a capacity and governance issue, rather than a technology issue.

7. Conclusions

Phase 3 of this longitudinal research programme confirms all four Phase 2 results using real-world data collection of 25 institutions (half of target sample). Barriers are critical, data format inconsistency, low technical competency, and inadequate infrastructure, elucidate why institutional AI tool adoption has been low even with the seemingly transformative potential.

Conclusions are evident: The AI tools cannot be implemented by IQACs without systemic reforms. Before implementing technology, IQAC leaders should focus on standardization of data format, assessment of the infrastructure, and training of staff. Policymakers need to harmonize data requirements on regulations, finance infrastructural developments and develop national capacity-building programmes. The education systems should not underestimate that adoption of technology is essentially a governance/capacity challenge, not a technology challenge.

The next phase of the research will proceed to Phase 4 that will formulate implementation frameworks based on these validation findings and convert them into practical guidance to institutions at different stages of adoption. The way towards AI-powered institutional quality assurance is not fast or technology-based; it must be gradual, systematically based, and intensive in change management.

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