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# IQA-AI: A CONCEPTUAL FRAMEWORK FOR AI-RESPONSIVE INTERNAL QUALITY ASSURANCE IN VIETNAMESE UNIVERSITIES OF TECHNOLOGY AND ENGINEERING

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**ABSTRACT**

***Generative artificial intelligence (AI) challenges a foundational assumption of internal quality assurance (IQA): an assessed artefact can no longer be treated automatically as trustworthy evidence of a learner's own competence. This article develops IQA-AI, a conceptual framework for AI-responsive IQA in Vietnamese universities of technology and engineering. The research combines structured document analysis and an international framework crosswalk of ESG 2015, AUN-QA 3.0 and UNESCO guidance with an exploratory descriptive comparison of five Vietnamese institutions. The institutional dataset covers three enabling conditions: doctoral-qualified faculty, internet bandwidth per 1,000 students and the proportion of accredited programmes. Substantial cross-institutional variation was observed, with coefficients of variation of 46.1%, 47.0% and 40.6%, respectively. These data do not measure AI readiness directly, but empirically support a differentiated rather than uniform implementation pathway. The proposed framework comprises six connected components: institutional AI policy, AI-responsive learning outcomes, authentic assessment, academic integrity and AI ethics, quality data governance, and continuous improvement with accountability. A three-phase roadmap links baseline diagnosis, controlled piloting and evidence-based scaling. The study contributes an analytically traceable framework and context-grounded recommendations, while recognising that effectiveness must be tested through expert validation and institutional pilots.***

***Keyword: internal quality assurance, generative artificial intelligence, engineering education, authentic assessment, academic integrity, data governance***

## 1. INTRODUCTION

Generative AI is changing higher education through content generation, personalised support, automated feedback and data analysis. It also creates risks concerning reliability, bias, privacy, authorship and academic integrity [1]–[3]. When AI contributes to essays, source code, engineering designs, simulations or reports, the submitted product may no longer represent the learner's unaided competence. The problem therefore extends beyond misconduct detection: it affects the validity of assessment evidence and the quality judgments derived from that evidence.

IQA has evolved from periodic compliance for external accreditation toward continuous, data-informed institutional governance. ESG 2015 and AUN-QA 3.0 connect quality policy, programme design, assessment, information management, stakeholder participation and improvement [4], [5]. However, these frameworks predate widespread generative AI and do not specify how AI use should be governed in assessment or quality-data processes. UNESCO provides principles for human-centred, transparent and accountable AI, but it is not an operational IQA framework [1], [2], [6].

Existing research has concentrated largely on teaching, student support, assessment and academic integrity [3], [7], [8]. Recent work has begun to connect AI integration with quality assurance [9], yet limited attention has been given to the institutional chain linking learning outcomes, assessment authenticity, evidence reliability, data governance and improvement. This gap is especially important in technology and engineering education, where students produce code, technical drawings, simulations, experimental data and integrated design projects that generative systems can partially create.

Accordingly, this study addresses three questions: (RQ1) Which AI-related IQA requirements are directly or indirectly covered by ESG 2015, AUN-QA 3.0 and UNESCO guidance? (RQ2) What institutional conditions in selected Vietnamese technology and engineering universities affect implementation? (RQ3) How can the identified gaps and contextual variation be translated into an operational conceptual framework and a staged roadmap? The contribution is IQA-AI: an AI-responsive layer that extends, rather than replaces, existing IQA arrangements.

## 2. CONCEPTUAL BACKGROUND

### *2.1. IQA as improvement governance*

In contemporary higher education, IQA is a permanent governance function rather than a dossier-production activity undertaken only for accreditation. Its value lies in converting standards, assessment evidence and stakeholder information into traceable decisions and verified improvement. ESG 2015 organises this logic through quality policy, programme design, student-centred learning and assessment, staff development, information management, public information and periodic review [4]. AUN-QA 3.0 connects strategic QA, systemic QA and institutional results [5]. Together, the frameworks imply a recurring sequence of setting standards, implementation, evidence collection, evaluation, improvement and accountability.

### *2.2. Generative AI and the IQA evidence chain*

Generative AI affects two foundations of IQA: the authenticity of learner assessment and the trustworthiness of quality evidence. Product-only assessment is increasingly insufficient; process evidence, oral defence, reflection, version histories and disclosure of AI assistance may be needed to establish authorship and competence [3], [7]. Academic integrity also moves beyond text matching toward transparent, authorised and accountable use of AI [8].

AI may support feedback analysis, risk identification and self-evaluation reporting, but unverified outputs can introduce error, bias or fabricated evidence. Processing learner data further requires lawful access, privacy protection, security, bias control and human accountability [1], [6]. AI-responsive IQA must therefore preserve traceability from intended outcomes to assessment, evidence, quality judgment and improvement action.

### *2.3. Technology and engineering education*

Technology and engineering programmes emphasise practice, experimentation, design and complex problem-solving. Their assessment artefacts include software, circuit diagrams, CAD/CAM/BIM models, laboratory records, simulations and capstone designs. Because generative AI can assist each of these outputs, a technically correct product does not by itself establish that the learner can explain assumptions, verify safety, diagnose failure or defend design decisions. This makes process-sensitive assessment and evidence governance central IQA concerns rather than optional teaching techniques.

## 3. METHODOLOGY

### *3.1. Research design*

A sequential design was used: (i) structured analysis of international reference documents; (ii) cross-framework coding; (iii) exploratory descriptive analysis of institutional enabling conditions; and (iv) conceptual synthesis. The design provides empirical contextual grounding without claiming causal validation of the proposed framework.

### *3.2. Framework corpus and coding*

The analytical corpus comprised ESG 2015, AUN-QA institutional assessment version 3.0, the UNESCO Recommendation on the Ethics of Artificial Intelligence, UNESCO guidance for generative AI in education and research, and the UNESCO AI competency framework for teachers [1], [2], [4]–[6]. Documents were coded against five dimensions derived from the problem analysis: AI policy and governance, assessment design, academic integrity, quality-data governance and staff capability. Coverage was classified as direct, indirect foundation or not explicit. The crosswalk was then used to identify requirements that could not be operationalised by any single source.

### *3.3. Exploratory institutional comparison*

The empirical component used secondary data from five Vietnamese institutions with technology and engineering missions: Vinh University of Technology and Engineering (SKV), Nam Dinh

University of Technology Education (SKN), University of Technology and Education–The University of Danang (DSK), Ho Chi Minh City University of Technology and Engineering (UTE), and Electric Power University (DDL). The purposive sample provides comparable disciplinary orientation and variation in scale and QA development. Data were compiled from institutional disclosure and QA records available up to 31 December 2024.

Three indicators were analysed: doctoral-qualified faculty (%), internet bandwidth per 1,000 students (Mbps), and accredited programmes (%). They represent academic capacity, basic digital infrastructure and QA institutionalisation. Mean, range, sample standard deviation and coefficient of variation (CV) were calculated. These indicators are enabling conditions, not direct measures of AI competence or IQA-AI maturity; therefore, they are used only to test whether a uniform implementation assumption is defensible.

### *3.4. Analytical boundaries*

The framework synthesis and the institutional comparison answer different questions. The crosswalk identifies the content required for AI-responsive IQA; the empirical comparison examines contextual heterogeneity relevant to implementation. No readiness ranking is produced, equal indicator weights are not assumed, and absence of a public document is not treated as evidence that an institutional practice does not exist.

## 4. RESULTS

### *4.1. Cross-framework analysis*

| Dimension | ESG/AUN-QA contribution | UNESCO contribution |
|---|---|---|
| AI policy | Quality policy, strategy and accountability | Human-centred, transparent and responsible AI |
| Assessment | Outcome alignment, fairness and consistency | Process evidence, disclosure and human oversight |
| Integrity | Indirect foundation in fairness/transparency | Ethics, authorship and user responsibility |
| Data | Information for evaluation and decisions | Privacy, security, bias and risk control |
| Staff capability | Professional development and HR strategy | Understand, use, evaluate and govern AI |

*Table 1. Crosswalk of AI-responsive IQA requirements*

ESG and AUN-QA provide the operational quality cycle but do not make generative-AI risks explicit. UNESCO directly addresses responsible AI principles but does not define institutional QA criteria, evidence or review procedures. The sources are therefore complementary: IQA-AI must preserve the established improvement cycle while making AI-specific controls observable and auditable.

### *4.2. Empirical variation in enabling conditions*

| Institution | Doctoral staff (%) | Mbps/1,000 students | Accredited programmes (%) |
|---|---|---|---|
| SKV | 17.48 | 166.70 | 79.28 |
| SKN | 17.69 | 170.00 | 90.91 |
| DSK | 38.60 | 433.70 | 58.33 |
| UTE | 43.30 | 217.40 | 52.92 |
| DDL | 52.00 | 200.00 | 26.30 |

*Table 2. Institutional enabling conditions (cut-off: 31 December 2024)*

*Source: authors' calculations from institutional disclosure and QA records [11]–[15].*

| Indicator | Mean | Range | SD | CV (%) |
|---|---|---|---|---|
| Doctoral staff | 33.81 | 17.48–52.00 | 15.58 | 46.1 |
| Bandwidth | 237.56 | 166.70–433.70 | 111.66 | 47.0 |
| Accredited programmes | 61.55 | 26.30–90.91 | 25.02 | 40.6 |

*Table 3. Descriptive variation across the five institutions*

Variation is substantial for all three indicators. Doctoral-qualified faculty ranged from 17.48% to 52.00% (CV=46.1%); bandwidth ranged from 166.70 to 433.70 Mbps per 1,000 students (CV=47.0%); and the proportion of accredited programmes ranged from 26.30% to 90.91% (CV=40.6%). No institution dominated all indicators: for example, the institution with the widest accreditation coverage did not have the highest doctoral share or bandwidth. This pattern empirically rejects a one-size-fits-all implementation assumption.

The indicators also reveal why infrastructure proxies should not be equated with AI readiness. Bandwidth permits digital activity but does not establish data standards, access control or model-risk oversight. Accreditation experience demonstrates QA institutionalisation but not AI-responsive assessment. Doctoral qualifications indicate academic capacity but not pedagogical or governance competence in AI. A baseline audit must therefore directly assess the six IQA-AI components before interventions are selected

### *4.3. Evidence-to-recommendation traceability*

| Observed finding | Supported recommendation | Claim boundary |
|---|---|---|
| High variation across all enabling indicators | Use staged and institution-specific implementation | Supports differentiation, not framework effectiveness |
| No case leads on every indicator | Conduct a component-level baseline audit | Indicators cannot be merged into a readiness rank |
| Digital capacity differs from QA coverage | Separate data governance from general infrastructure | Bandwidth is not a governance measure |
| QA experience differs from AI capability | Pilot AI-responsive assessment before scaling | Accreditation does not demonstrate AI readiness |

*Table 4. Empirical findings and bounded recommendations*

## 5. THE IQA-AI CONCEPTUAL FRAMEWORK

IQA-AI is proposed as an AI-responsive layer within existing IQA rather than a parallel assurance system. Six components restore traceability between competence, assessment, evidence, data-based judgment and improvement. Staff AI competence is a cross-cutting enabling condition.

| Component | Core function | Principal evidence |
|---|---|---|
| 1. Institutional AI policy | Define permitted use, roles, data protection, oversight and risk controls | Policy, regulations, assigned owner, risk register |
| 2. AI-responsive outcomes | Embed responsible use, verification, critical judgment and professional ethics | PLO–CLO mapping, syllabi, attainment results |

| | | |
|---|---|---|
| 3. Authentic assessment | Combine product quality with process, explanation, reflection and disclosure | Rubrics, portfolios, oral defence, version history |
| 4. Integrity and AI ethics | Set boundaries for authorship, attribution and investigation | Integrity rules, disclosure form, verification procedure |
| 5. Quality-data governance | Standardise, secure, authorise and audit data use | Data catalogue, access matrix, logs, IQA dashboard |
| 6. Improvement and accountability | Convert verified analysis into monitored action | Decision records, action plans, follow-up evidence |

*Table 5. Components and observable evidence of IQA-AI*

### *5.1. Institutional AI policy*

Policy should define purpose, permitted and prohibited uses, responsibilities, privacy safeguards, human oversight and risk escalation. It should be integrated into academic regulations, quality policy and digital-transformation governance rather than issued as an isolated technology guideline [6], [10].

### *5.2. AI-responsive learning outcomes*

Programme and course outcomes should specify the level at which learners must use, evaluate and verify AI. In engineering programmes, this includes testing generated code, checking design feasibility and safety, documenting assumptions and accepting professional accountability for AI-assisted decisions.

### *5.3. Authentic assessment in AI-enabled environments*

Assessment should combine outputs with evidence of reasoning and production. Appropriate mechanisms include staged submissions, design logs, repositories, oral defence, laboratory observation, reflection and AI-use disclosure. The objective is not to prohibit AI universally, but to maintain valid inferences about learner competence [3], [7].

### *5.4. Academic integrity and AI ethics*

Integrity rules must distinguish authorised assistance from substitution of assessed thinking. They should address attribution, confidentiality, intellectual property, verification and proportionate investigation. Automated AI-detection scores should not be treated as conclusive evidence without human review [8].

### *5.5. Quality-data governance*

Data from learning-management, student-information, assessment, laboratory and stakeholder systems should be standardised and linked under explicit access and retention rules. AI-supported analytics require provenance, validation, bias checks, audit logs and accountable approval before results inform institutional decisions [1], [2].

### *5.6. Continuous improvement and accountability*

Verified information should enter a Plan–Do–Check–Act cycle: define the quality problem and indicators; conduct a bounded intervention; check outcomes, risks and stakeholder feedback; and adjust policy, curriculum or assessment. AI may support analysis, but authorised humans retain professional judgment and final accountability.

## 6. GOVERNANCE IMPLICATIONS AND ROADMAP

The empirical comparison supports differentiated implementation. Institutions with established QA routines but limited academic capacity may prioritise staff development and small assessment pilots. Institutions with stronger digital infrastructure should not scale analytics before data ownership, access, quality and audit controls are defined. Accreditation coverage can facilitate procedural integration, but it cannot substitute for direct evidence of responsible AI governance.

| Phase | Priority actions | Decision evidence |
|---|---|---|
| 1. Diagnose and prepare | Audit six components; assign ownership; review policy, data and competence; define pilot scope | Baseline report, risk register, pilot protocol |
| 2. Pilot and evaluate | Test outcomes, process-sensitive assessment, disclosure and governed analytics in selected programmes | Validity, workload, incidents, feedback and data-quality results |
| 3. Institutionalise and scale | Revise rules; integrate effective practices into IQA; expand with periodic review | Approved procedures, monitored improvements and accountability records |

*Table 6. Three-phase implementation roadmap*

Progression between phases should depend on evidence, not elapsed time. A pilot should be revised or stopped when assessment validity is not improved, staff workload becomes disproportionate, data risks are unresolved or stakeholder trust declines. This decision rule converts the roadmap from a generic recommendation into a testable governance process.

## 7. DISCUSSION

The study reframes generative AI as a quality-evidence problem. The central issue is not whether an institution adopts AI, but whether it can still justify the inference that an assessed artefact evidences the intended competence and that quality data support defensible decisions. This framing connects assessment validity, academic integrity and data governance within the IQA improvement cycle.

The crosswalk demonstrates that no reviewed framework is sufficient alone. ESG and AUN-QA provide institutional QA logic; UNESCO provides AI-governance principles. IQA-AI operationalises their intersection through components and observable evidence. The descriptive institutional results add an implementation insight: large variation in enabling conditions makes uniform mandates inefficient and potentially unsafe. Recommendations are therefore bounded to what the evidence supports—baseline diagnosis, controlled piloting, component-specific improvement and evidence-based scaling.

The empirical component remains exploratory. The sample is small and purposive; the indicators rely on secondary records and do not directly measure AI policies, staff AI competence, assessment validity, data-governance maturity or implementation outcomes. The document coding was not subjected to independent intercoder reliability testing. Future research should validate component relevance with experts, develop and test an IQA-AI measurement instrument, and conduct longitudinal pilots comparing assessment validity, incident rates, staff workload, data quality and stakeholder trust before and after implementation.

## 8. CONCLUSION

Generative AI weakens the previously assumed relationship between submitted products, learner competence and trustworthy IQA evidence. Through a structured crosswalk of international frameworks and an exploratory comparison of five Vietnamese technology and engineering universities, this study develops IQA-AI as a six-component conceptual framework. The institutional data show substantial heterogeneity in academic capacity, digital infrastructure and QA institutionalisation, supporting a differentiated three-phase roadmap rather than uniform implementation. The framework offers traceable requirements and evidence for policy, outcomes, assessment, integrity, data governance and improvement. Its effectiveness, however, remains a proposition for empirical testing rather than an established result.

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