Using AI for quality assurance processes in higher education – opportunities and perceptions in transformation

Master Thesis

Submitted to:
The International Graduate Center of Bremen University of Applied Sciences

In partial Fulfillment of the requirements for the degree
Master of Arts - Management - Digitalization and Transformation

Submitted by: Mehreen Irfan Ali
Woltmershauser Straße 261
28197, Bremen
Matriculation No.: 5402386

First Examiner: Fynn Wolken
Second Examiner: Prof. Dr. Vera de Hesselle

Date of Submission: 16th March, 2026

The following thesis contains confidential data. Publications or copies of the work including extracts are not permitted without the explicit permission of the FIBAA. The thesis may be accessible only to the examiners and the members of the Examination Committee.

I. Acknowledgements

I would like to express my sincere gratitude to my thesis examiners for their invaluable guidance, insightful feedback and continuous support. Their expertise and thoughtful recommendations greatly contributed to the development and successful completion of this thesis.

I would also like to extend my heartfelt appreciation to FIBAA for their cooperation and support during the course of this research. In particular, I am deeply grateful to Christiane Butler and Michael Stephan for their constant encouragement, openness, and willingness to share their time and knowledge. Their valuable insights and support played a significant role in shaping this project.

Finally, I would like to thank my family and friends for their unwavering encouragement, patience and understanding throughout this academic journey. Their support has been a constant source of motivation and strength.

II. Table of Contents

III. List of Figures

IV. List of Tables

V. List of Abbreviations

EHEA	European Higher Education Area
ENQA	European Association for Quality Assurance in Higher Education
EQAR	European Quality Assurance Register
ESG	Standards and Guidelines for Quality Assurance in the European Higher Education Area
F-ACC	FIBAA Accreditation and Certification Committee
FIBAA	Foundation for International Business Administration Accreditation
HEI	Higher Education Institutions
QA	Quality Assurance
TAM	Technology Acceptance Model
IS	Information Systems
CRM	Customer Relationship Management System
GDPR	General Data Protection Regulation
ECTS	European Credit Transfer and Accumulation System

1. Abstract

Artificial intelligence (AI) is increasingly discussed as a tool for improving administrative efficiency and analytical capacity in higher education governance. However, its potential role within quality assurance (QA) processes remains under-explored. QA agencies operate within highly regulated environments where professional judgement, institutional legitimacy, and stakeholder trust are central to decision-making.

This study investigates the opportunities, limitations, and organizational readiness for AI adoption within higher education quality assurance. A qualitative case study was conducted at the accreditation agency FIBAA. Data were collected through semi-structured interviews with internal and external stakeholders, complemented by observations of accreditation procedures and document analysis. The material was analyzed using coding techniques to identify patterns in stakeholder perceptions and operational workflows.

The findings show that stakeholders largely support AI as a tool for procedural augmentation, particularly for tasks such as document screening, information retrieval, and administrative coordination. At the same time, strong resistance exists toward delegating evaluative judgement to AI systems. Accreditation decisions are widely understood as interpretive and context-dependent processes that require expert assessment and collective deliberation. As a result, AI adoption is viewed as conditional and bounded by institutional norms, governance structures and the need to preserve the legitimacy of QA outcomes.

The study contributes to research on organizational AI readiness by demonstrating how technological adoption in governance-oriented institutions is shaped not only by technical feasibility but also by professional identity, regulatory frameworks and stakeholder trust.

Keywords: artificial intelligence, quality assurance, accreditation, higher education governance, organizational AI readiness

2. Introduction

Digital transformation is fundamentally reshaping higher education systems, influencing not only teaching and learning practices but also the mechanisms through which academic quality is evaluated and assured. The higher education sector is currently undergoing substantial transformation driven by digitalization, evolving labour market demands and increasing global competition. Universities and professional learning providers are increasingly expected to respond rapidly to changing skill requirements by continuously updating degree programs, introducing new study formats and offering more flexible learning opportunities that support lifelong learning and continuous upskilling and reskilling. In addition to traditional degree programs, institutions and training providers increasingly offer shorter courses and modular learning opportunities that allow learners to acquire specific competencies in a more flexible manner. While such developments increase flexibility within education systems, they also add complexity to the processes through which academic quality, transparency and comparability must be ensured.[1]

Within this evolving landscape, quality assurance (QA) agencies play a central role in safeguarding academic standards, maintaining institutional credibility and supporting continuous improvement across higher education and professional learning systems.[2] As educational offerings diversify and learning formats become more flexible and modular, QA agencies must manage increasingly complex, data-intensive and time-sensitive evaluation processes.

Despite these developments, QA procedures remain largely human-centric. Core activities such as accreditation procedures, documentation reviews, evaluation coordination and report preparation continue to rely heavily on manual work and extensive documentation. These processes require significant human involvement, expert judgement and administrative coordination, often supported by fragmented or semi-digital systems. While this human-centered approach ensures academic rigor and

[1] European Higher Education Area (EHEA) (2024). Tirana Communiqué. https://ehea.info/Immagini/Tirana-Communique.pdf.

[2] ENQA (2015). Standards and Guidelines for Quality Assurance in the European Higher Education Area ESG. https://www.enqa.eu/wp-content/uploads/2015/11/ESG_2015.pdf.

contextual understanding, it also creates operational challenges, including high workloads, long processing times and limited scalability.

At the same time, artificial intelligence (AI) has emerged as a key driver of organizational transformation across many sectors. AI technologies offer capabilities such as automated document analysis, large-scale data processing, pattern recognition and decision support, all of which have the potential to enhance efficiency and consistency in administrative and evaluation-related tasks.[3] However, in contrast to sectors such as finance, healthcare, or business administration, the application of AI within higher education QA remains relatively limited and under-explored.

Within this context, this study focuses on FIBAA as a case organization to explore the opportunities and perceptions associated with AI-supported transformation in QA processes. It is an established accreditation and certification agency, governed under EU regulations, and operating across international higher education and professional education environments. FIBAA works with a wide range of organizations, including universities, professional academies and digital learning platforms. It's structured evaluation procedures, strong reliance on human expert assessment and increasing exposure to digitalization pressures make it a suitable case for examining how AI may influence QA work practices.

Using a qualitative research approach, this study explores how AI is perceived by internal and external stakeholders within the organization and identifies potential opportunities for supporting or enhancing existing QA processes. Particular attention is given to organizational perceptions, employee attitudes and concerns related to trust, ethics, transparency and the evolving role of human expertise in AI-supported environments.

Building on these insights, the research further conducts an AI readiness analysis to assess the extent to which the organization is prepared for AI integration from strategic, organizational and cultural perspectives. By combining insights on perceived opportunities with an assessment of readiness conditions, the study aims to contribute to a deeper understanding of how QA agencies can navigate digital transformation while maintaining their core values. The findings are intended not only to support FIBAA's

---

[3] Makridakis, S. (2017). The Forthcoming Artificial Intelligence (AI) revolution: Its Impact on Society and Firms. *Futures*, 90(90), pp.46–60. doi:https://doi.org/10.1016/j.futures.2017.03.006.

ongoing transformation efforts but also to provide insights relevant for other QA agencies facing similar challenges across higher education and professional education systems.

2.1. Problem Statement

Quality assurance agencies in higher education are under increasing pressure to digitalize their processes in response to growing regulatory complexity, expanding international accreditation activities and emerging educational formats such as micro-credentials. While artificial intelligence offers potential benefits for managing large volumes of documentation, data analysis and administrative coordination, QA processes remain fundamentally human-centered, relying on expert judgement, interpretive authority and institutional legitimacy. The introduction of AI into such evaluative governance systems therefore raises important questions concerning trust, professional responsibility and organizational readiness. There remains limited empirical understanding of how stakeholder perceptions and institutional conditions shape the responsible integration of AI within QA workflows.

2.2. Research Objectives

The primary objective of this study is to examine how artificial intelligence could be integrated into quality assurance processes in higher education using FIBAA as a sample organization, with a specific focus on opportunities, organizational perceptions and readiness for transformation.

To achieve this aim, the study pursues the following objectives:

- To explore perceived opportunities and challenges associated with the use of AI in quality assurance processes
- To examine stakeholder perceptions of AI associated change within the quality assurance agency
- To assess the organizational readiness for AI adoption from a strategic, cultural and operational perspective
- To identify specific areas within quality assurance processes where AI support may be considered appropriate and beneficial.

2.3. Research questions

Main Question: How do stakeholder perceptions and organizational readiness shape the responsible integration of artificial intelligence in higher education quality assurance processes?

Subquestions:

- What opportunities and challenges are associated with the use of AI in quality assurance processes in higher education?
- How do internal and external stakeholders perceive the integration of AI within quality assurance activities?
- Which areas of quality assurance processes are perceived as suitable for AI support without compromising academic integrity and ethical standards?
- To what extent is the organization prepared for the adoption of AI in terms of strategic, cultural and operational readiness?

2.4. Scope and limitations of the study

This study adopts a qualitative case study approach to explore perceptions, opportunities and organizational readiness related to the use of artificial intelligence in higher education QA. Empirically, the research is limited to FIBAA, which serves as an illustrative case within the QA context.

The analysis focuses on stakeholder perceptions of AI, potential application areas within QA workflows, and conditions influencing organizational readiness. The study does not include the implementation or technical evaluation of specific AI systems, nor does it aim to assess long-term impacts on job roles or workforce structures. As a qualitative single-case study, the findings aim for analytical rather than statistical generalization.

2.5. Significance of this study

This research intends to contribute to the limited body of academic literature on the application of AI in higher education QA by shifting the focus from technological capabilities to organizational perspectives and readiness. It addresses an existing research gap by examining how AI-driven transformation is perceived within a QA agency.

From a practical standpoint, the findings offer FIBAA reflective insights that may support strategic discussions on digital transformation and responsible AI adoption. More broadly, the study provides transferable considerations for QA agencies seeking to navigate AI-driven change while preserving human judgment, transparency and academic integrity as required under the ESG.[4]

2.6. Structure of the thesis

This thesis is structured into five chapters.

The first, introduces the research problem, outlines the objectives and research questions and defines the scope of the study.

The second, reviews relevant literature on artificial intelligence, digital transformation and QA in higher education. It further introduces the theoretical frameworks that guide the analysis, including technology acceptance, sociotechnical systems and organizational change perspectives.

The third, describes the methodological approach, including the qualitative case study design, data collection methods, coding procedures and considerations of research quality and limitations.

The fourth, presents the empirical findings derived from stakeholder interviews and document analysis. The results are structured thematically and include the development of an integrated AI adoption model and an AI readiness framework for the case organization.

The last chapter, discusses the findings in relation to the theoretical frameworks, outlines practical implications and a phased implementation pathway, and concludes with the study's contributions, limitations and directions for future research.

3. Literature Review

The literature review addresses three core areas: (1) key concepts related to AI and digital transformation, (2) the role and challenges of QA in higher education and (3) organizational perspectives on AI adoption, including perceptions, readiness and ethical considerations. In addition, relevant theoretical frameworks are introduced to support the analysis of the empirical findings.

[4] ENQA (2015)

3.1. Artificial Intelligence and Digital Transformation

Academic literature commonly defines artificial intelligence as a class of digital systems capable of performing tasks that typically require human cognitive abilities, such as learning from data, pattern recognition, prediction and decision support.[5] Rather than constituting a single technology, AI encompasses a broad set of techniques and applications that are increasingly embedded in organizational information systems.

AI research highlights that AI is predominantly conceptualized as a data-driven and probabilistic technology that supports, augments, or restructures organizational processes.[6] This literature emphasizes the importance of distinguishing AI from traditional rule-based automation. While automation relies on predefined instructions, AI systems are characterized by their ability to adapt based on data inputs and generate context-sensitive outputs.[7]

It is important to point out that AI implementation is not merely like bringing in a technical artifact, but it is an organizational phenomenon whose impact depends on how it is embedded within existing workflows, decision-making structures and professional practices.[8] As such, AI is increasingly viewed as a complementary technology that augments human expertise rather than replacing it, particularly in knowledge-intensive and evaluative domains.

Digital transformation is widely understood as the process through which organizations integrate digital technologies to fundamentally reshape processes, structures and value creation mechanisms.[9] Within this context, AI is recognized as a key enabling

---

[5] Makridakis (2017)

[6] Collins, C., Dennehy, D., Conboy, K. and Mikalef, P. (2021). Artificial Intelligence in Information Systems research: a Systematic Literature Review and Research Agenda. *International Journal of Information Management*, 60(102383). doi:https://doi.org/10.1016/j.ijinfomgt.2021.102383.

[7] Jöhnk, J., Weißert, M. and Wyrtki, K. (2021). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, 63, pp.5–20. doi:https://doi.org/10.1007/s12599-020-00676-7.

[8] Collins et al. (2021)

[9] Vial, G. (2019). Understanding Digital transformation: a Review and a Research Agenda. The Journal of Strategic Information Systems, 28(2), pp.118–144. doi:https://doi.org/10.1016/j.jsis.2019.01.003.

technology due to its potential to support advanced data analysis, process optimization and decision support across organizational functions.[10]

However, empirical research stresses that AI-driven digital transformation extends far beyond technological deployment. Studies show that the outcomes of AI adoption are strongly influenced by organizational strategy, governance arrangements and employee acceptance.[11] From a sociotechnical perspective, AI implementation requires alignment between technical systems and social structures in order to generate sustainable organizational value.[12]

The literature also highlights persistent challenges associated with AI-enabled transformation, including concerns related to transparency, explainability, accountability and ethical responsibility.[13] These challenges are particularly important and concerning in evaluation-oriented and public-interest domains, where decision-making processes must remain interpretable and trustworthy. In response, regulatory initiatives such as the European Union Artificial Intelligence Act[14] aim to establish risk-based governance frameworks that ensure transparency, human oversight and responsible deployment of AI systems in sensitive domains.

Overall, research suggests that the transformative potential of AI is highly context-dependent. Rather than producing uniform outcomes, AI adoption is shaped by organizational goals, stakeholder perceptions and readiness conditions.[15] This insight underscores the importance of examining AI within specific organizational and process

---

[10] Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N. and Haenlein, M. (2021). Digital transformation: a Multidisciplinary Reflection and Research Agenda. Journal of Business Research, 122, pp.889–901. doi:https://doi.org/10.1016/j.jbusres.2019.09.022.

[11] Jöhnk, Weißert and Wyrtki (2021)

[12] Sarker, S., Chatterjee, S., Xiao, X. and Elbanna, A. (2019). The Sociotechnical Axis of Cohesion for the IS Discipline: Its Historical Legacy and Its Continued Relevance. MIS Quarterly, 43(3), pp.695–719. doi:https://doi.org/10.25300/misq/2019/13747.

[13] Stahl, B.C., Andreou, A., Brey, P., Hatzakis, T., Kirichenko, A., Macnish, K., Laulhé Shaelou, S., Patel, A., Ryan, M. and Wright, D. (2021). Artificial intelligence for human flourishing – Beyond principles for machine learning. Journal of Business Research, 124, pp.374–388. doi:https://doi.org/10.1016/j.jbusres.2020.11.030.

[14] European Parliament, Council of the European Union (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). http://data.europa.eu/eli/reg/2024/1689/oj.

[15] Collins et al. (2021)

contexts, which is central to the focus of the present study. Another important insight emerging from the AI adoption literature is that the integration of AI technologies typically occurs as a gradual organizational process rather than a single implementation event.[16] This perspective suggests that AI adoption is best understood as a phased transformation process in which organizations gradually expand the scope and complexity of AI applications as capabilities mature. Consequently, many organizations adopt structured implementation approaches that introduce AI incrementally, allowing learning, governance mechanisms and stakeholder acceptance to develop over time.. Successful AI deployment therefore requires the progressive development of readiness across multiple dimensions, including technological infrastructure, data management capabilities, organizational processes and employee competencies.

3.2. Quality Assurance in Higher Education

3.2.1.Purpose and Role of Quality Assurance Agencies

QA in higher education is commonly understood as a systematic set of processes aimed at monitoring, evaluating and enhancing the quality of academic provision and institutional performance. The literature emphasizes that QA serves both accountability and improvement-oriented functions, ensuring transparency toward external stakeholders while supporting internal quality development within higher education institutions.[17]

Research highlights that QA agencies play an intermediary role between higher education institutions, governments and society by translating quality expectations into formalized evaluation processes.[18] Importantly, QA is widely understood as a socially embedded and expert-driven activity rather than a purely technical compliance mechanism. Accreditation and evaluation processes depend on peer review, deliberation

---

[16] Uren, V. and Edwards, J.S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68(1), p.102588. doi:https://doi.org/10.1016/j.ijinfomgt.2022.102588.

[17] Harvey, L. and Williams, J. (2010). Fifteen Years ofQuality in Higher Education. Quality in Higher Education, 16(1), pp.3–36. doi:https://doi.org/10.1080/13538321003679457.

[18] Stensaker, B. (2007). Quality as Fashion: Exploring the Translation of a Management Idea into Higher Education. In: D.F. Westerheijden, B. Stensaker and M.J. Rosa PhD, eds., Quality Assurance in Higher Education. Springer, Dordrecht, pp.99–118. doi:https://doi.org/10.1007/978-1-4020-6012-0_4.

and the contextual interpretation of standards, all of which are embedded within institutional norms and professional communities.[19] In this sense, QA outcomes are not produced through mechanical rule application but through structured expert judgement operating within a governance framework. This human-centered and interpretive character has significant implications for the integration of digital technologies, particularly AI, which must align with established professional authority structures rather than replace them.

3.2.2. Challenges in Quality Assurance Processes

QA systems in higher education have expanded in scope and complexity. Comparative research shows that increasing accountability demands, internationalization and performance-based governance have substantially intensified QA activities and reporting requirements.[20] As a result, QA processes have become increasingly resource-intensive for both agencies and institutions. It is observed that QA practices rely heavily on manual documentation, extensive reporting cycles and fragmented data management, which can reduce efficiency and limit the strategic use of quality-related information[21]. These challenges are particularly evident in accreditation processes that involve large volumes of qualitative documentation and coordination among multiple stakeholders.

Recent developments in higher education have further increased the pressure on existing QA systems. In particular, the growing emergence of micro-credentials has introduced new forms of educational provision that challenge traditional quality assurance models. Micro-credentials are commonly defined as short, modular learning units designed to certify specific skills or competencies acquired through targeted learning activities rather than full degree programs.[22] They are typically more flexible, shorter in duration

---

[19] Stensaker, B. and Harvey, L. eds., (2011). Accountability in Higher Education Global Perspectives on Trust and Power. Routledge, pp.1–22.

[20] Cardoso, S., Rosa, M.J. and Stensaker, B. (2015). Why is quality in higher education not achieved? The view of academics. Assessment & Evaluation in Higher Education, 41(6), pp.950–965. doi:https://doi.org/10.1080/02602938.2015.1052775.

[21] Manatos, M.J., Rosa, M.J. and Sarrico, C.S. (2015). The importance and degree of implementation of the European standards and guidelines for internal quality assurance in universities: the views of Portuguese academics. Tertiary Education and Management, 21(3), pp.245–261. doi:https://doi.org/10.1080/13583883.2015.1061587.

[22] OECD (2023). Quality and value of micro-credentials in higher education. *OECD Publishing*, 66. doi:https://doi.org/10.1787/9c4b7b68-en.

and focused on clearly defined learning outcomes, allowing learners to acquire specific professional competencies within shorter timeframes. The increasing importance of micro-credentials is closely linked to broader transformations in labour markets and lifelong learning systems, where individuals must continuously update their skills in response to rapid technological and economic change.

The expansion of digital learning platforms and industry-led training initiatives has further accelerated the growth of micro-credentials. Major online learning platforms such as Coursera now offer professional certificates in collaboration with universities and employers, while technology companies such as Google provide widely recognized career certificates in areas including data analytics, cybersecurity and IT support. Within the European higher education landscape, policymakers have begun exploring ways to integrate micro-credentials within existing frameworks, including potential alignment with the European Credit Transfer and Accumulation System (ECTS) and evaluation mechanisms guided by the Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG).[23] These developments signal a shift toward more modular, flexible and digitally delivered forms of higher education.

However, the growing number and diversity of micro-credentials also creates new challenges for QA systems. Unlike traditional degree programs, which are typically evaluated periodically through structured accreditation cycles, micro-credentials can be developed and delivered at a much higher frequency and across a wider range of providers. This expansion significantly increases the volume of educational offerings that must be evaluated and monitored. As institutions introduce large numbers of micro-credentials across different formats and delivery modes, QA agencies must assess a broader range of programs within shorter development cycles and across more diverse institutional contexts.[24] Consequently, traditional QA mechanisms designed primarily for the evaluation of full degree programs face increasing pressure to become more scalable and adaptable.

At the such a time, researchers especially caution that excessive formalization and bureaucratization of QA may weaken its perceived legitimacy within academic

[23] ENQA (2015)

[24] Ahsan, K., Akbar, S., Kam, B. and Abdulrahman, M.D.-A. (2023). Implementation of micro-credentials in higher education: A systematic literature review. *Education and Information Technologies*, 28, pp.13505–13540. doi:https://doi.org/10.1007/s10639-023-11739-z.

communities. When QA is experienced primarily as a compliance exercise, it risks shifting focus away from meaningful quality enhancement toward procedural conformity.[25] Balancing accountability with improvement therefore remains a persistent challenge for QA systems.

3.2.3. Digitalization and Human-Centricity in Quality Assurance

Although digital tools have increasingly been introduced into higher education administration, research suggests that QA processes remain largely human-centric. Core activities such as evaluation, peer review and accreditation decision-making continue to depend on expert judgment, dialogue and contextual understanding.[26]

Existing studies show that digitalization in QA has so far focused mainly on administrative support functions, such as document submission platforms and communication tools, rather than on analytical or decision-support technologies.[27] Consequently, while digital systems may streamline certain tasks, they have not fundamentally transformed the underlying logic of QA processes.

Trust, transparency and interpretability are absolutely crucial for the acceptance of QA outcomes because these decisions can have significant institutional and reputational consequences. Stakeholders, especially governing agencies and the academic community, place high importance on human involvement and explainable evaluation practices.[28] These characteristics make QA a particularly sensitive context for advanced digital technologies and underscore the need for careful examination of AI adoption within the agencies.

---

[25] Beerkens, M. (2015). Quality Assurance in the Political context: in the Midst of Different Expectations and Conflicting Goals. Quality in Higher Education, 21(3), pp.231–250. doi:https://doi.org/10.1080/13538322.2015.1111004.

[26] Stensaker and Harvey (2011, pp.1–22)

[27] Manatos, Rosa and Sarrico (2015)

[28] Beerkens (2015)

3.3. Artificial Intelligence in Higher Education Quality Assurance

3.3.1. AI Applications in Higher Education Administration

Research on artificial intelligence in higher education has primarily focused on teaching, learning analytics and student support. However, a growing body of literature highlights the increasing relevance of AI for administrative and governance-related functions within higher education systems. Studies show that AI applications in administration commonly target tasks such as document management, information retrieval, pattern recognition in large datasets and decision-support activities.[29]

Within administrative contexts, AI is often framed as an efficiency-enhancing technology that supports data-intensive and repetitive processes rather than replacing expert judgment. Empirical studies suggest that AI can assist organizations by improving consistency, reducing manual workloads and enabling more systematic use of institutional data.[30] These characteristics are particularly relevant for QA processes considering the extensive documentation, long evaluation cycles and coordination among with multiple stakeholders. Nevertheless, it can be noted that the adoption of AI in higher education administration remains uneven and experimental.

3.3.2. Opportunities of AI for Quality Assurance Processes

Several potential opportunities for applying AI in QA contexts have been identified. AI-supported tools may enhance the handling and analysis of large volumes of accreditation documentation, support the identification of patterns across evaluation reports, and improve process transparency through structured data management. It is suggested that AI can contribute to consistency and reliability in evaluation-related tasks

---

[29] Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019). Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where are the Educators? International Journal of Educational Technology in Higher Education, 16(39). doi:https://doi.org/10.1186/s41239-019-0171-0.

[30] Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. British Journal of Management, 30(2), pp.272–298. doi:https://doi.org/10.1111/1467-8551.12343.

by reducing variability in information processing and supporting evidence-based decision-making.[31]

Artificial intelligence may also support expert evaluators in situations where disciplinary knowledge gaps exist. In complex professional decision environments, AI systems are increasingly conceptualized as tools that augment human expertise by retrieving relevant knowledge, synthesizing large information sources, and supporting sense-making in unfamiliar domains. Research on hybrid intelligence suggests that combining human judgement with AI-supported information processing can improve decision quality in contexts where expertise is incomplete or distributed.[32] Studies on artificial intelligence in higher education similarly highlight that AI technologies can assist professionals by analyzing large volumes of information, identifying relevant patterns and supporting evidence-based decision-making processes[33]. In the context of higher education QA, such capabilities may assist expert panels in interpreting specialized program content, regulatory frameworks, or disciplinary standards that fall outside their immediate areas of expertise, while preserving the central role of human judgement in final accreditation decisions.

One significant opportunity identified in recent research concerns the potential for artificial intelligence to enable more proactive approaches to QA.[34] Traditional QA systems, as previously discussed, typically rely on periodic review cycles in which institutions are evaluated after programs have been implemented, meaning that quality issues are often identified retrospectively. Advances in AI-driven analytics, however, allow large volumes of institutional data to be analyzed continuously, enabling earlier detection of patterns, risks and emerging quality concerns. By integrating multiple sources of institutional data and applying predictive analytical techniques, AI-supported systems may assist QA bodies in identifying potential challenges before they affect

---

[31] Jöhnk, Weißert and Wyrtki (2021)

[32] Dellermann, D., Ebel, P., Söllner, M. and Leimeister, J.M. (2019). Hybrid Intelligence. *Business & Information Systems Engineering*, 61, pp.637–643. doi:https://doi.org/10.1007/s12599-019-00595-2.

[33] Zawacki-Richter et al. (2019)

[34] Warren, S.J., Boston Vogt, E., Tincher, B. and Yang, J. (2025). Enhancing quality assurance through strategic artificial intelligence integration: a framework for higher education digital transformation. *Quality Assurance in Education*, 34(2). doi:https://doi.org/10.1108/qae-09-2024-0183.

educational outcomes. In this sense, AI technologies have been suggested as a means of shifting QA practices from predominantly reactive evaluation toward more proactive and data-informed quality management.

3.3.3. Challenges, Risks and Ethical Considerations

Alongside potential benefits, the literature highlights significant challenges and risks associated with the use of AI in QA. It points out that AI systems are opaque and difficult to interpret, which creates governance problems because, decision logic cannot be easily explained, accountability becomes unclear and stakeholders may not trust algorithmic outcomes.[35]

Transparency and explainability are frequently cited as critical concerns, particularly in contexts where evaluative decisions carry institutional and reputational consequences. Stakeholders will be reluctant to accept AI-supported evaluations if decision logic is not interpretable or if accountability becomes unclear.

Bias and data quality represent additional challenges. Research indicates that AI systems may reproduce or amplify existing biases embedded in training data and digital infrastructures, raising concerns for decision-making contexts that require fairness and accountability.[36] As a result, scholars caution against uncritical adoption of AI in governance-related domains.

From an organizational perspective, ethical concerns are closely linked to trust and acceptance. Employees' perceptions of AI, concerns about professional autonomy, and uncertainty about responsibility distribution can significantly influence the feasibility of AI integration.[37] These issues reinforce the importance of examining AI adoption through a human-centered and organizational lens.

3.4. Organizational Perceptions and Readiness for AI Adoption

Research on artificial intelligence adoption consistently highlights organizational readiness as a critical precondition for successful implementation. Rather than referring

---

35 Stahl et al. (2021)

36 Kak , A. and West, Dr.S.M. (2023). *Confronting tech power 2023 Landscape*. [online] AI Now Institute. Available at: https://ainowinstitute.org/2023-landscape.

37 Jöhnk, Weißert and Wyrtki (2021)

solely to technical infrastructure, readiness encompasses strategic prioritization, leadership commitment, data governance capacity, and the development of organizational competencies required to integrate AI into existing workflows.[38] In governance-oriented institutions, these dimensions are particularly significant because AI adoption intersects with accountability structures and formal decision-making responsibilities. Studies examining AI implementation in the public sector similarly emphasize that successful integration requires not only technological capabilities but also appropriate governance frameworks, institutional capacities and mechanisms to ensure transparency, oversight and responsible use of algorithmic systems.[39] These findings suggest that organizations operating in regulatory or evaluative contexts must carefully align technological innovation with institutional norms, professional responsibilities and established decision-making processes when introducing AI-supported systems. Without such alignment, AI initiatives often remain experimental or symbolic rather than becoming embedded in core operational practices.[40]

In QA environments, readiness is additionally shaped by the interpretive and evaluative character of core activities. Because accreditation decisions carry reputational and regulatory consequences, the introduction of AI requires clear governance frameworks, transparency mechanisms and role definitions that delineate technological support from human authority.[41] Consequently, AI adoption in such contexts is contingent not only on technical feasibility but also on institutional legitimacy and stakeholder trust.

Taken together, the literature suggests that AI integration in QA agencies depends on multidimensional readiness conditions that extend beyond technological capability.

---

[38] Wirtz, B.W., Weyerer, J.C. and Geyer, C. (2019). Artificial Intelligence and the Public Sector —Applications and Challenges. *International Journal of Public Administration*, 42(7), pp.596–615. doi:https://doi.org/10.1080/01900692.2018.1498103.

[39] Mergel, I., Dickinson, H., Stenvall, J. and Gascó, M. (2023). Implementing AI in the public sector. *Public Management Review*, pp.1–14. doi:https://doi.org/10.1080/14719037.2023.2231950.

[40] Mergel, I., Edelmann, N. and Haug, N. (2019). Defining digital transformation: Results from expert interviews. Government Information Quarterly, 36(4), p.101385. doi:https://doi.org/10.1016/j.giq.2019.06.002.

[41] ENQA (2015)

3.4.1.Stakeholder Perceptions of AI

Stakeholder perceptions of artificial intelligence in governance and education-related contexts are shaped less by technological capability and more by institutional values, accountability requirements and normative expectations. In contrast to commercial settings, stakeholders in public-sector and educational environments tend to evaluate AI through questions of legitimacy, responsibility, transparency and trust rather than performance optimization alone.[42] These perceptions are influenced by the institutional context in which technologies are introduced, where decision-making processes often carry formal accountability and reputational consequences.

Perceptions of AI also differ markedly across stakeholder groups within organizations. Strategic and managerial actors often frame AI as an opportunity to improve efficiency, consistency and scalability, particularly in data-intensive administrative tasks. In contrast, professional and expert stakeholders tend to focus on the implications of AI for professional judgement, discretion and ethical responsibility. These differences reflect divergent institutional roles, accountability relationships and risk perceptions rather than simply individual attitudes toward technology. In governance-oriented organizations, such distinctions are particularly significant because technological support may intersect with established professional authority and responsibility structures.

Research further demonstrates that acceptance of AI is highly task-dependent. Studies examining multi-stakeholder perspectives in educational contexts show that AI is more readily perceived as legitimate when applied to supportive or preparatory activities, while skepticism increases when AI is associated with evaluative or decision-making functions.[43] This distinction is particularly relevant for QA environments, where processes rely heavily on expert interpretation, professional judgement and the possibility of contestation between stakeholders.

Importantly, the literature cautions against interpreting critical or ambivalent perceptions of AI as resistance to innovation. Rather, skepticism often reflects a deliberate effort to safeguard institutional values such as fairness, explainability,

---

[42] Neumann, Guirguis and Steiner (2024); Wirtz, Weyerer and Geyer (2019)

[43] Karran, A.J., Charland, P., Trempe-Martineau, J., Ortiz de Guinea Lopez de Arana, A., Lesage, A.-M., Sénécal, S. and Léger, P.-M. (2025). Multi-stakeholder Perspective on Responsible Artificial Intelligence and Acceptability in Education. *npj Science of Learning*, 10(1). doi:https://doi.org/10.1038/s41539-025-00333-2.

procedural accountability and the credibility of evaluation processes. In this sense, stakeholder perceptions function as a form of institutional sense-making that shapes how, where and under what conditions AI can be legitimately integrated into organizational workflows.

3.4.2. AI Readiness and Digital Maturity

In response to the limitations of perception and acceptance focused approaches, recent studies increasingly emphasize organizational readiness as a key determinant of successful AI adoption. AI readiness is commonly conceptualized as a multidimensional condition encompassing technological infrastructure, data governance, human competencies, organizational structures and strategic alignment.[44]

Research in public-sector and governance-oriented organizations highlights that digital maturity does not automatically translate into AI readiness. While many organizations possess basic digital systems, they often lack integrated data architectures, clear ownership of digital processes and institutional frameworks for responsible AI use.[45] As a result, AI initiatives frequently remain fragmented, experimental, or symbolic rather than becoming embedded in core organizational workflows.

Studies further indicate that AI readiness is strongly shaped by organizational capacity to align AI initiatives with existing decision-making structures and accountability mechanisms. Neumann et al. (2024)[46] demonstrate that organizations with higher levels of digital maturity are better able to critically assess where AI can add value and where human judgment must remain central. Conversely, low maturity environments face a higher risk of adopting AI without a clear understanding of its implications for responsibility distribution and governance.

Crucially, readiness is not a static state but an evolving and negotiated process. Jöhnk et al. (2021)[47] argues that readiness develops through organizational learning, experimentation and continuous reassessment of technological and ethical implications. In governance-oriented contexts such as QA, readiness is inseparable from questions of

---

[44] Jöhnk, Weißert and Wyrtki (2021)

[45] Mergel et al. (2023)

[46] Neumann, Guirguis and Steiner (2024)

[47] Jöhnk, Weißert and Wyrtki (2021)

legitimacy, transparency and institutional trust. This suggests that assessing AI readiness requires more than technical audits; it necessitates understanding how organizational actors interpret AI in relation to their professional roles and institutional responsibilities.

Taken together, the literature positions AI readiness and digital maturity as socio-organizational constructs rather than purely technical conditions. This perspective provides a robust foundation for examining how readiness is perceived, constructed and enacted within QA agencies, and directly informs the empirical focus of the present study.

3.5. Theoretical Framework

Recent research has begun to explore structured approaches for integrating artificial intelligence into higher education QA systems. For example, Warren et al. (2025)[48] propose a strategic framework describing how AI can support operational processes, decision-support activities and strategic quality analytics within accreditation systems. While this model highlights important functional opportunities for AI integration, it remains primarily practice-oriented. In contrast, the present study adopts a stronger theoretical foundation by combining the Technology Acceptance Model, sociotechnical systems theory and organizational sense-making perspectives in order to better capture the organizational, human and institutional dynamics shaping AI adoption in QA contexts.

3.5.1. Technology Acceptance Model (TAM)

As previously established stakeholder perceptions of AI in QA contexts are complex and often ambivalent. TAM offers a convenient lens for examining these perceptions by focusing on perceived usefulness and perceived ease of use.[49] TAM helps to explain

---

[48] Warren, S.J., Boston Vogt, E., Tincher, B. and Yang, J. (2025). Enhancing quality assurance through strategic artificial intelligence integration: a framework for higher education digital transformation. *Quality Assurance in Education*, 34(2). doi:https://doi.org/10.1108/qae-09-2024-0183.

[49] Davis, F.D. (1989). Perceived usefulness, Perceived Ease of use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), pp.319–340. doi:https://doi.org/10.2307/249008.
Venkatesh, V. and Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), pp.186–204. doi:https://doi.org/10.1287/mnsc.46.2.186.11926.

why AI is more readily perceived as acceptable in supportive, administrative tasks than in evaluative or decision-making functions.

At the same time, the reviewed literature clearly indicates that acceptance alone does not explain AI adoption in QA agencies. Concerns related to transparency, accountability and professional judgment extend beyond the explanatory scope of traditional acceptance models. For this reason, TAM is used in this study diagnostically rather than predictively, supporting the interpretation of stakeholder perceptions without assuming a direct link between acceptance and adoption.

3.5.2. Sociotechnical IS Perspective on AI

AI should be understood as an organizational phenomenon whose impact depends on how it is embedded within existing workflows, decision structures and professional practices.[50] This insight aligns closely with sociotechnical information systems (IS) perspectives, which conceptualize AI as part of an interdependent system of social and technical elements.[51]

In the context of QA, AI-supported tools would intersect directly with expert judgment, peer review processes and institutional accountability arrangements. A sociotechnical perspective therefore provides an appropriate theoretical lens for analyzing tensions between efficiency-oriented technological capabilities and the need to preserve transparency, interpretability and human oversight. This approach allows the study to examine not whether AI can be implemented, but how and under what conditions AI may be perceived as legitimate and appropriate.

By positioning sociotechnical IS theory as the core analytical lens, the study directly addresses the human-centric and judgment-intensive nature of QA in Higher Education.

3.5.3. Organizational Sense-making and AI Readiness

The literature on artificial intelligence adoption increasingly emphasizes that organizational readiness is not solely determined by technical infrastructure or digital maturity. Instead, readiness develops through processes of interpretation, learning and organizational adaptation as actors make sense of how AI systems interact with existing

---

[50] Berente, N., Gu, B., Recker, J. and Santhanam, R. (2021). Managing Artificial Intelligence. MIS Quarterly, 45(3), pp.1433–1450. doi:https://doi.org/10.25300/MISQ/2021/16274.

[51] Sarker et al. (2019)

work practices and decision-making structures. In this view, AI adoption is better understood as an evolving organizational phenomenon rather than a discrete technological implementation.[52]

Information systems(IS) research further conceptualizes AI integration as a form of organizational sense-making in which employees and decision-makers continuously interpret the implications of algorithmic systems for professional roles, coordination mechanisms and institutional responsibilities. Faraj, Pachidi and Sayegh (2018)[53] argue that learning algorithms reshape organizational work by redistributing knowledge, authority and expertise, requiring organizations to renegotiate how human and machine capabilities interact in everyday practices. As a result, AI implementation involves not only technical deployment but also adjustments in organizational routines, governance arrangements and professional expectations.

From this perspective, skepticism or caution toward AI reflects active sense-making processes through which organizational actors assess how AI aligns with institutional values, accountability requirements and professional norms. This dynamic is particularly significant in governance-oriented environments such as higher education QA, where evaluative decisions carry reputational and regulatory consequences.

Taken together, this literature suggests that understanding AI adoption requires examining how organizations interpret and integrate algorithmic systems within existing professional and institutional contexts. Rather than assuming that technological capability alone determines adoption outcomes, scholars emphasize the importance of examining how actors negotiate the role of AI within established governance structures and work practices. This perspective provides the conceptual foundation for the present study, and its investigation on how AI opportunities and readiness conditions are interpreted by stakeholders within a higher education QA agency.

---

[52] Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P.V., Janssen, M., Jones, P., Kar, A.K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B. and Medaglia, R. (2021). Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging challenges, opportunities, and Agenda for research, Practice and Policy. *International Journal of Information Management*, 57, p.101994. doi:https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

[53] Faraj, S., Pachidi, S. and Sayegh, K. (2018). Working and Organizing in the Age of the Learning Algorithm. *Information and Organization*, 28(1), pp.62–70. doi:https://doi.org/10.1016/j.infoandorg.2018.02.005.

3.6. Research Gap

Empirical research focusing specifically on QA agencies, rather than higher education institutions, is limited. Furthermore, while perceptions and readiness are widely acknowledged as critical, there is insufficient qualitative research examining how these dynamics are constructed and negotiated within QA organizations. Finally, AI readiness is often treated abstractly, with limited empirical attention to how it manifests in human-centric, evaluative settings.

This study addresses these gaps by examining AI opportunities and readiness within a QA agency through a qualitative research approach. In doing so, it extends current research beyond institutional contexts and contributes context-sensitive insights into AI adoption in governance-oriented QA processes.

4. Methodology

4.1. Research design

This study adopts a qualitative research design to explore the opportunities, perceptions and organizational implications of AI in higher education QA processes. Qualitative research is particularly suitable for investigating complex organizational phenomena where interpretation, professional judgement and institutional context shape decision-making processes.[54]

The research is structured as an interpretive case study focusing on FIBAA as a model QA agency. Case study research is appropriate for examining contemporary organizational practices within their real-life context. The potential integration of AI into QA organization represents such a context-dependent phenomenon, shaped by regulatory frameworks, professional norms and organizational routines.

Data were collected through multiple qualitative sources, including semi-structured interviews with internal and external stakeholders, observation of selected accreditation and certification procedures, and document analysis of guidelines and internal process documentation. Semi-structured interviews allow researchers to explore participants' interpretations and experiences while maintaining flexibility to probe emerging

[54] Yin, R.K. (2017). Case Study Research and Applications: Design and Methods. 6th ed. Thousand Oaks, California: Sage Publications.

themes.[55] Document analysis further supports understanding of formal procedures and organizational structures by examining institutional texts and operational materials.[56]

The use of multiple sources of evidence enabled methodological triangulation, which strengthens the credibility of qualitative findings by allowing insights to be compared and validated across different forms of data.[57] Data analysis followed an inductive coding approach that identifies patterns and conceptual categories emerging from the empirical material.[58] The methodological approach therefore draws on principles of grounded theory coding procedures,[59] all the while remaining analytically guided by established theoretical frameworks in information systems and organizational change.

4.2. Research Context

FIBAA (Foundation for International Business Administration Accreditation) serves as the empirical context of this study. The organization is an established European QA agency operating within both national and international higher education systems. Its accreditation activities are embedded within the governance framework of the European Higher Education Area (EHEA) and aligned with the Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG)[60], which define common principles for internal and external QA across Bologna Process member states. FIBAA has undergone external review against these standards and is listed in the European Quality Assurance Register for Higher Education (EQAR), confirming compliance with recognized European QA requirements. This institutional positioning

---

[55] Myers, M.D. (2009). Qualitative Research in Business & Management. 2nd ed. SAGE Publications Ltd. doi:https://doi.org/10.4135/9781036208417.

[56] Bowen, G.A. (2009). Document Analysis as a Qualitative Research Method. *Qualitative Research Journal*, 9(2), pp.27–40. doi:https://doi.org/10.3316/QRJ0902027.

[57] Fusch, P., Fusch, G. and Ness, L. (2018). Denzin's Paradigm Shift: Revisiting Triangulation in Qualitative Research. *Journal of Social Change*, 10(1), pp.19–32. doi:https://doi.org/10.5590/JOSC.2018.10.1.02.

[58] Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, 16(1), pp.15–31. doi:https://doi.org/10.1177/1094428112452151.

[59] Strauss, A. and Corbin, J. (2008). Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory. 3rd ed. SAGE Publications. doi:https://doi.org/10.4135/9781452230153.

[60] ENQA (2015)

situates the organization within a system of transnational higher education governance and reinforces the legitimacy of its accreditation decisions.

FIBAA provides a range of QA services including program accreditation, institutional accreditation, system accreditation and certification of continuing education programs. In addition to traditional university degree programs, the organization also evaluates executive education, professional training programs and digital learning formats offered by universities and external education providers. Recent developments in higher education have led to the increasing emergence of short-form learning credentials, commonly referred to as micro-credentials.[61] As these and other modular learning formats expand, QA agencies are expected to evaluate a growing number of smaller, more flexible educational offerings. This development places additional pressure on QA systems to operate more efficiently and at greater scale while maintaining the credibility and rigor of evaluation processes.

FIBAA's operational scope is international. The organization conducts QA procedures across more than thirty countries and collaborates with higher education institutions and educational providers in Europe, Central Asia and Southeast Asia. Procedures have been conducted in countries including Germany, Austria, Switzerland, the Netherlands, Kazakhstan, Indonesia and Vietnam. Operating across such diverse regulatory and cultural environments requires balancing standardized QA criteria with contextual interpretation by expert panels and accreditation commissions.

At the organizational level, FIBAA is currently engaged in broader digital transformation initiatives. These include the development of a centralized customer relationship management (CRM) system intended to streamline interactions with institutions, experts and partner organizations. The organization also uses digital collaboration and project management tools, such as Asana, to coordinate QA workflows and internal communication. In parallel, internal discussions have begun regarding the potential role of artificial intelligence in supporting certain administrative tasks within QA processes. In response, FIBAA has initiated internal training sessions aimed at improving staff awareness of AI technologies and the regulatory implications of their potential use.

---

[61] Council of the European Union (2022). *A European approach to micro-credentials for lifelong learning and employability*. [online] Official Journal of the European Union. Available at: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32022H0627.

Despite these digital initiatives, the QA processes at FIBAA remain strongly human-centered. Evaluation procedures rely on structured criteria, peer-review-based expert assessments, and final decision-making by the FIBAA Accreditation and Certification Committee. The process typically involves extensive documentation review, institutional self-evaluation reports, expert reviews and formal evaluation reports. As a result, professional judgement, transparency and regulatory alignment remain central features of the QA process and directly shape the conditions under which digital technologies, including AI, may be integrated into QA workflows.

4.2.1. Stakeholder Environment of FIBAA

From a stakeholder theory perspective, organizations operate within networks of actors who influence or are affected by their activities.[62] Understanding these relationships helps clarify how governance structures shape organizational processes and the potential adoption of technological innovations.

Within FIBAA, several internal stakeholders contribute to different levels of decision-making and operational implementation. The Foundation Board represents the highest governing authority and determines the strategic direction and overarching organizational policies of the agency. Executive leadership and division managers are responsible for major internal operational decisions and organizational coordination. The FIBAA Accreditation and Certification Committee (F-ACC) serves as the central decision body, making final QA outcome decisions and defining the evaluation criteria used within its procedures. Expert panels, composed of academics, industry professionals and student representatives, conduct peer-review evaluations and provide independent assessments that inform these decisions. At the operational level, project managers coordinate the QA process, manage documentation, liaise with institutions, and implement the procedural aspects of QA.

Externally, FIBAA's most central stakeholders are its clients, including higher education institutions and continuing education providers that seek quality seals for their programs, institutional quality systems, or professional education offerings. At the same time, regulatory and oversight bodies such as ENQA, EQAR and national authorities define the standards and compliance requirements under which the agency operates.

[62] Freeman, R.E. (1984). Strategic Management: a Stakeholder Approach. Boston: Pitman.

Together, these internal and external stakeholders form a governance network in which strategic direction, regulatory expectations, and client needs interact to shape how QA processes are conducted and how innovations such as artificial intelligence may be considered within QA workflows.

4.3. Data collection methods

To investigate this context empirically, a multi-method qualitative data collection strategy was employed.

4.3.1. Semi-Structured Interviews

The primary data source for this study consisted of semi-structured interviews with internal and external stakeholders of FIBAA. This deemed appropriate considering the goal, exploring perceptions, experiences and organizational sense making processes, as they allow for depth while maintaining thematic focus.[63]

Eleven in-depth interviews were conducted. Two participants were invited to each interview, each interview lasted approximately one hour, was audio-recorded and transcribed for analysis. Participants were purposefully selected to represent different organizational roles and stakeholder perspectives. There was one interview with the executive leadership, including the managing director and deputy managing director, there were five interviews with different project managers, representing multiple divisions, two interviews with division managers and deputy division managers, also representing different departments in the organization, one with members of the F-ACC who are also take part in QA processes as experts, and two interviews with clients, representing different types of educational institutions. This purposive sampling strategy ensured that perspectives from operational, strategic and evaluative levels were captured.[64]

Two distinct interview guides were developed: one for internal and another for external stakeholders (See Appendix II). The guides included open-ended questions addressing current digital workflows, perceptions of AI integration, perceived opportunities and risks, organizational openness toward innovation and future visions of QA processes.

---

[63] Kvale, S. and Brinkmann, S. (2015). InterViews: Learning the Craft of Qualitative Research Interviewing. 3rd ed. SAGE Publications Ltd.

[64] Myers (2009)

While the interview structure ensured comparability across participants, the flexible format allowed for probing and elaboration where relevant themes emerged.[65]

4.3.2. Observational Insights

In addition to interviews, observational insights were gathered through participation in and observation of two QA procedures, spanning the process from initial documentation submission to the final evaluation conference. Observing these procedures provided direct insight into workflow dynamics, expert panels and the structure of deliberative decision-making.

In this study, observations helped contextualize how the QA processes unfold operationally and provided insight into the interaction between formal guidelines and everyday working practices.

These observational insights were not treated as standalone data but were used to complement interview findings and to better understand the operational environment in which stakeholders form their perceptions of AI and digitalization. Combined with interviews and document analysis, the observations contributed to methodological triangulation, strengthening the credibility of the empirical findings by allowing multiple perspectives on the same organizational processes.[66]

4.4. Data analysis

Data analysis followed a structured and iterative qualitative coding process inspired by grounded theory procedures.[67] The objective was not to generate a fully emergent theory independent of prior frameworks, but rather to develop categories that could later be interpreted in relation to the established theoretical models in information systems and organizational change.

All interview transcripts were analyzed manually. The analysis progressed through three interconnected stages: open coding, axial coding and theoretical integration. Throughout the process, constant comparison was applied, meaning that new data were continuously

---

65 Kvale and Brinkmann (2015)

66 Fusch, Fusch and Ness (2018)

67 Strauss and Corbin (2008)

compared with previously coded segments in order to refine categories and identify relationships.[68]

4.4.1. Open Coding

In the first stage, transcripts were examined line-by-line to identify meaningful units of analysis. Codes were assigned to statements reflecting stakeholder perceptions, experiences, tensions, and expectations regarding AI use, digitalization and QA processes.

Open coding remained close to participants' language and no attempt was made to impose predefined theoretical categories. Instead, recurring patterns were allowed to emerge inductively from the data. Codes captured themes such as workload pressures, trust in expert judgement, concerns about bias, perceptions of efficiency, legitimacy considerations, and organizational openness toward digital tools.

This stage generated a broad pool of first-order codes representing diverse stakeholder viewpoints across operational, managerial and evaluative roles.

4.4.2. Axial Coding

In the second stage, the codes were examined for conceptual relationships and grouped into higher-order categories. Following Strauss and Corbin's (1998)[69] approach, axial coding focused on identifying conditions, interactions and consequences that structured stakeholder perceptions.

Rather than treating themes as isolated observations, this phase examined how categories related to one another. For example, expressions of enthusiasm for automation were frequently accompanied by concerns about preserving human judgement authority. Similarly, calls for process acceleration were often balanced by reflections on legitimacy and prestige.

Through iterative comparison across stakeholder groups, several central analytical categories were developed, including:

- AI as procedural infrastructure

[68] Gioia, Corley and Hamilton (2013)

[69] Strauss, A. and Corbin, J. (2008). Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory. 3rd ed. SAGE Publications. doi:https://doi.org/10.4135/9781452230153.

- Professional judgement authority
- Acceleration vs. legitimacy tension
- Contextual precision requirements
- Implementation and alignment gaps

These categories reflected recurring tensions between efficiency and legitimacy, automation and expertise, and innovation and institutional identity.

Importantly, variation across stakeholder groups was preserved during this stage to avoid homogenizing perspectives.

4.4.3. Theoretical Integration

In the final stage, empirically derived categories were interpreted in relation to established theoretical frameworks. The purpose of this step was not to force data into predefined models, but to assess how existing theory could help explain observed patterns.

Three theoretical lenses guided this interpretive integration:

First, the Technology Acceptance Model was used to examine how perceived usefulness and perceived ease of use shaped stakeholder openness toward AI. While TAM helped explain individual-level acceptance dynamics, it proved insufficient for capturing other concerns.

Second, sociotechnical systems theory provided a framework for understanding the interdependence between technical systems and social structures. This perspective was particularly useful in analyzing tensions between AI-enabled efficiency and the preservation of professional judgement authority.

Third, organizational change perspectives were applied to interpret implementation challenges, including uneven communication, training gaps and cultural adaptation processes.

4.4.4. Analytical Rigor

To enhance analytical credibility, several measures were employed. Constant comparison was maintained throughout coding to ensure internal coherence of categories.[70] Contradictory or skeptical viewpoints were deliberately retained and analyzed as negative cases, rather than being treated as outliers.

As coding progressed, later interviews reinforced rather than fundamentally altered the emerging category structure. The absence of substantially new thematic dimensions indicated conceptual saturation within the scope of the study.

4.5. Research Quality and Limitations

In qualitative research, trustworthiness is commonly evaluated in terms of credibility, dependability and confirmability rather than statistical validity.[71] Several measures were adopted to strengthen these dimensions.

First, methodological triangulation was employed through the combination of semi-structured interviews, observational insights and document analysis. Comparing multiple data sources enabled cross-verification of themes and reduced reliance on single-perspective interpretations.[72] Patterns identified in interviews were examined against observed workflows and formal process documentation, enhancing contextual depth.

Second, analytical rigor was supported through constant comparison during coding.[73] As analysis progressed, later interviews reinforced rather than fundamentally altered the emerging themes. The research was conducted in close collaboration with members of FIBAA, which facilitated access to stakeholders and internal procedures. At the same time, this proximity required deliberate awareness of potential interpretive bias. To mitigate this risk, structured interview guides were used, and alternative interpretations were considered during category development.

Despite these measures, the study has limitations. As a single-case study, findings are context-bound and cannot be statistically generalized. The purpose of the research, however, is analytical rather than statistical generalization.[74] The conceptual models and

[70] Glaser, B.G. and Strauss, A.L. (1967). The Discovery of Grounded Theory. Transaction Publishers.

[71] Gioia, Corley and Hamilton (2013)

[72] Fusch, Fusch and Ness (2018); Yin (2017)

[73] Glaser and Strauss (1967)

[74] Yin (2017)

readiness framework developed in this study may offer transferable insights for similar QA agencies operating in governance-oriented and evaluative environments.

Furthermore, the study focuses on stakeholder perceptions and organizational readiness rather than on measuring actual performance outcomes of AI implementation. The findings therefore reflect interpretive and anticipatory dimensions of AI adoption rather than empirically tested system effects.

4. Analysis & Findings

The findings are organized thematically based on the axial categories developed during qualitative coding. Rather than presenting stakeholder perspectives in isolation, the chapter adopts a comparative approach, highlighting convergences and divergences across stakeholder groups. This cross-case orientation allows for a more nuanced understanding of how AI adoption is interpreted at operational, strategic and evaluative levels within the organization.

The chapter first discusses, the current state of digitalization and existing AI use within QA workflows. Second, perceived opportunities of AI integration are examined. Third, stakeholder concerns and perceived risks are analyzed, with particular attention to the preservation of professional judgement authority and organizational legitimacy. Fourth, organizational readiness dynamics are assessed. Finally, the chapter synthesizes findings into an integrated AI adoption model and an empirically grounded AI readiness framework.

4.1. Current Digitalization and AI Use in Practice

The empirical data indicate that FIBAA is already operating within a substantially digitalized infrastructure, although artificial intelligence integration remains in an exploratory phase. Digital tools are deeply embedded in daily workflows, particularly in project coordination, documentation management and communication processes. However, AI use is currently limited to supportive and experimental functions rather than core evaluative activities.

Across interviews, Asana emerged as the central project management platform structuring QA procedures. Project managers described how Asana provides task transparency, deadline tracking and procedural standardization.

In addition, Microsoft-based tools, including Outlook, Teams, SharePoint and Word form the backbone of communication and document handling. Observational insights confirmed that most documentation exchange, expert coordination and internal review processes are digitally organized.

The introduction of a new customer relationship management (CRM) system represents a significant digital transformation initiative. While the executive leadership and selected departments are actively involved in its development, project managers reported limited insight into its current implementation stage. This suggests that digitalization initiatives are progressing unevenly across organizational units.

In contrast to structured digital tools, AI usage is more individualized and informal. Several project managers reported using Microsoft Copilot for language refinement, email drafting and summarizing lengthy university documentation. AI is primarily employed to improve clarity, tone and efficiency in written communication, particularly in international contexts where English is not always the primary working language. As one participant stated:

"I always write the first draft myself, but I use AI to improve phrasing and clarity."

Some participants described using AI tools to summarize extensive self-evaluation reports or to conduct preliminary background research on unfamiliar higher education systems. However, such use remains supplementary. AI outputs are consistently subject to manual verification and no participant reported relying on AI for evaluative judgement or decision-making.

Even when AI is used for summarizing large self-evaluation reports, participants emphasized the necessity of manual verification. A senior project manager noted:

"AI gives well-written sentences, but it doesn't understand what is really important for accreditation."

The executive leadership's perspectives reflect a strategic awareness of AI's broader potential. Discussions around developing an internal, domain-trained AI system in the far future suggest a long-term ambition to integrate AI into structured workflows. Yet even at the strategic level, AI is conceptualized as a supportive assistant rather than an autonomous evaluator.

"a permanent AI colleague who knows all our procedures and developments."

External stakeholders display varying degrees of AI familiarity. A client described intensive AI use within their own organizations, including AI-supported report writing and communication. While the other client, emphasized the importance of maintaining human-centered interaction during the QA processes. Despite these differences, there is no indication that stakeholders expect AI to replace expert judgement in QA decisions.

Overall, AI use within FIBAA can be characterized as controlled experimentation within a highly digitalized but professionally anchored environment. Digital infrastructure is mature in terms of workflow management, yet AI integration remains peripheral and supportive.

4.2. Perceived Opportunities of AI Integration

Across stakeholder groups, participants identified several areas in which AI could enhance existing QA processes. These perceived opportunities are concentrated primarily in procedural efficiency, documentation handling and structured analytical support rather than in core evaluative judgement.

4.2.1. Procedural Efficiency and Workflow Support

The most consistently identified opportunity concerns workflow optimization. Project managers described the QA process as highly structured but documentation-intensive, involving large volumes of self-evaluation reports, annexes, expert comments and iterative revisions. Several internal stakeholder highlighted the time-consuming nature of preliminary document checks, version control and report drafting.

AI-supported pre-check systems were frequently mentioned as a desirable enhancement. Internal and external stakeholders envisioned tools capable of verifying whether required documents were submitted, identifying missing sections, flagging inconsistencies, or generating structured summaries aligned with pre-set criteria. Such automation would not replace human review but could reduce time spent locating and organizing information.

"If the system could flag missing documents automatically, we wouldn't need so much back-and-forth."

Report drafting was another frequently cited area of potential support. While all stakeholders emphasized that final reports must remain human-authored and reviewed, many noted that the structure of the reports follows a relatively stable template. AI could assist in organizing content, ensuring logical coherence and reducing repetitive phrasing. Language refinement, particularly in international contexts, was already being supported through tools such as Copilot. A participant noted:

"The structure is always similar. AI could help make sure conditions are logically explained before the report goes to the division head."

Clients also recognized potential acceleration benefits. One client remarked:

"An AI agent could perform an initial review. That would speed up the whole quality assurance process."

Operational bottlenecks outside of core evaluation were also identified. Examples included the coordination of expert travel arrangements, handling automated email notifications and responding to recurring expert queries. Operational stakeholders including project managers and division managers, suggested that AI-supported prioritization systems or integrated digital assistants could reduce administrative overload in these areas.

Clients echoed the potential efficiency gains. One expressed openness to AI-supported initial document reviews, noting that early feedback on completeness or structural weaknesses could accelerate the overall process.

4.2.2. Analytical and Knowledge Support

Beyond administrative efficiency, the executive leadership and division managers identified opportunities for broader analytical support. Given FIBAA's long history and large archive of QA reports, participants described the possibility of AI-assisted meta-analysis across procedures.

Such capabilities could support thematic trend identification, comparative analysis across institutions, or historical tracking of conditions and recommendations. Executive leadership participants, in particular, envisioned AI as a strategic companion capable of synthesizing large datasets and informing future development initiatives. They described the possibility of conducting thematic meta-analysis across decades of QA reports. One representative described the vision as:

"Not just input-output correction, but analyzing meta-trends, where the market is going."

F-ACC members suggested that AI could help structure complex reports in direct alignment with the set criteria, thereby improving transparency and consistency in decision-making preparation. In cases involving unfamiliar contexts or regulatory frameworks, AI-supported background research was viewed as potentially valuable.

"Normally I would ask our experts, but AI helped me check the recent legal change independently."

Importantly, even in these more ambitious scenarios, AI was framed as analytical assistance rather than decision authority. Participants consistently drew a distinction between structured information processing and interpretive judgement.

4.2.3. Competitive Positioning and Strategic Advantage

Most stakeholders also linked AI integration to competitive positioning within the international QA market. As QA agencies operate in a partially competitive environment, efficiency gains and process transparency were perceived as potential advantages. Faster turnaround times and improved digital interfaces were viewed as factors that could enhance client satisfaction.

At the same time, all stakeholders clearly expressed awareness that automation must be balanced against maintaining credibility and trust. While efficiency was valued, it was not framed as an overriding objective independent of professional standards.

Overall, perceived opportunities for AI integration are concentrated in structured, repetitive and information-heavy aspects of QA processes. AI is predominantly imagined as a supportive infrastructure that enhances workflow efficiency, analytical capacity and strategic insight. Core evaluative functions, however, are consistently reserved for human expertise.

These opportunity structures must be understood in relation to the concerns and boundary conditions identified in the following section.

4.3. Perceived Risks and Boundary Conditions

While stakeholders identified meaningful opportunities for AI-supported efficiency, these were consistently accompanied by clearly articulated boundary conditions. AI integration was not framed as inherently problematic; rather, its legitimacy depended on preserving professional judgement, contextual precision, and institutional credibility.

Across interviews, concerns were not expressed as resistance to innovation per se, but as reflections on the limits of automation within evaluative governance processes.

4.3.1.Preservation of Professional Judgement Authority

The most pronounced boundary condition relates to the protection of human evaluative authority. F-ACC members (also, experts) and experienced project managers repeatedly emphasized that QA is fundamentally an interpretive process rather than a purely technical assessment. One commission member stated:

"Quality is not just facts. It is assessment. And assessment cannot be delivered by an AI system alone."

Participants described QA as involving nuanced judgement, contextual interpretation and deliberative reasoning that extend beyond structured criteria compliance. Conditions and recommendations are often shaped by disciplinary expertise, institutional context and professional experience. Several participants explicitly stated that while AI could assist in identifying patterns or summarizing information, final decisions must remain exclusively human-led.

This concern was particularly salient among commission-level stakeholders. AI was viewed as potentially useful for structuring information but insufficient for evaluating the adequacy of didactical concepts, institutional strategies, or academic coherence. In this sense, professional judgement authority functions as a clear boundary line: automation may support preparation, but decision-making remains human. As a F-ACC member put it:

"AI can help structure, but it cannot interpret what quality really means in a program."

4.3.2.Acceleration versus Legitimacy Tension

A second recurring theme concerns the relationship between efficiency and perceived value. While faster processes were often described as desirable from an operational standpoint, most stakeholders expressed mixed feelings regarding excessive acceleration. One senior project manager reflected:

"If something this valuable only takes two months instead of nine, it feels slightly wrong."

Another referred to international QA procedures where length contributes to prestige:

“They were proud of the long and difficult process. Faster is not necessarily better.”

Accreditation is typically conducted in cycles and requires substantial preparation effort from universities. Some stakeholders noted that if the process were dramatically shortened, it might risk appearing less rigorous or less prestigious. The duration and intensity of QA were implicitly associated with its symbolic value.

This perception was reinforced by examples of highly selective international QA systems where lengthy procedures contribute to perceived prestige. As such, speed is not unconditionally equated with improvement. Instead, stakeholders articulated a tension between process optimization and maintaining the credibility and ritual significance of QA.

4.3.3.Contextual Precision and Domain Specificity

Many participants questioned whether current AI systems are capable of capturing the high level of contextual specificity required in QA assessments. QA involves detailed examination and cross-examination of program structures, student facilitation systems, legal frameworks, examination regulations and national higher education systems.

Several project managers reported unsuccessful attempts to use AI for simple comparison tasks, such as identifying overlaps between study programs or assessing compliance with specific didactical criteria. While AI-generated outputs were often linguistically coherent, they were described as lacking substantive precision. One project manager described:

“It produced beautiful sentences, but it didn’t understand the distinctions. The content is too specific.”

Another highlighted legal complexity:

“In Germany especially, we have very detailed legal frameworks. AI would need to be trained exactly for that.”

Commission members also noted that AI systems may struggle to account for cultural, political, or regulatory differences across countries. Given FIBAA’s extensive international portfolio, contextual awareness is considered essential. As a result, stakeholders expressed caution toward relying on generic large language models without domain-specific training.

4.3.4.Authenticity and Perceptions of AI-Generated Content

Another significant concern relates to perceptions of authenticity. Several participants described a perceptible difference between human-authored and AI-generated texts. Even when AI-generated language was polished and structurally sound, some stakeholders reported a sense of reduced authenticity or diminished intellectual effort. One participant observed:

"When I recognize that something was written by AI, I subconsciously rate it slightly lower."

This perception extended to the evaluation of self-evaluation reports submitted by universities.

"The report was well written, but I wondered if they had really reflected on it or just expanded bullet points with AI."

When participants suspected that large portions were generated by AI, questions arose regarding the depth of institutional reflection underlying the document. Although such concerns were acknowledged as partly subjective and potentially transitional, they illustrate that AI integration intersects not only with efficiency considerations but also with cultural norms regarding effort and authorship.

4.3.5.Governance, Transparency and Data Considerations

Finally, participants raised practical governance concerns. These included uncertainty regarding permissible AI use under data protection regulations like the GDPR, lack of structured internal guidelines, and uneven communication regarding digital transformation initiatives.

While most participants reported anonymizing data when using external AI tools, awareness of regulatory boundaries varied. The development of internal AI systems was seen as a potential solution, but questions of training data, consent, and governance remain unresolved.

Overall, stakeholder concerns do not reflect categorical opposition to AI integration. Instead, they delineate a structured set of boundary conditions within which AI may be considered legitimate. Professional judgement authority, contextual precision, institutional legitimacy and governance clarity emerge as central constraints shaping acceptable forms of automation and AI implementation.

These boundary conditions interact directly with the perceived opportunities identified earlier and form the foundation for understanding organizational readiness dynamics.

4.4. Organizational Readiness and Cultural Dynamics

The preceding sections demonstrate that AI integration is neither categorically embraced nor rejected within FIBAA. Rather, readiness emerges as uneven across strategic, operational and cultural dimensions.

4.4.1. Strategic Openness and Competitive Awareness

Participants in strategic roles emphasized the need to engage proactively with digital transformation to remain competitive in the international QA market. As a division manager stated:

"If we don't approach this in a constructive way, others will, and then we will have to catch up."

AI was described not merely as a tool for internal efficiency but as a structural development influencing the broader higher education landscape. This framing indicates a high degree of strategic awareness and openness at the organizational apex.

At the same time, AI was envisioned as an assistant or companion rather than as an autonomous evaluator. Strategic openness is therefore accompanied by a clearly defined conceptual boundary regarding decision authority.

4.4.2. Operational Workload and Conditional Acceptance

At the operational level, readiness appears strongly linked to workload pressures. Project managers repeatedly highlighted high documentation volume, repetitive coordination tasks and administrative burdens. Within this context, AI is often perceived pragmatically as a potential workload relief mechanism.

One senior project manager pointed-out:

"Most colleagues are very open, because everyone has a high workload. Any tool that saves time would be welcome."

However, operational acceptance remains conditional. Internal stakeholders, especially emphasized that AI must demonstrably improve efficiency without increasing complexity or requiring disproportionate oversight. Uncertainty regarding CRM implementation and uneven communication about digital initiatives suggest that readiness may be influenced by perceived alignment between technological change and daily practice.

4.4.3.Training Gaps and Knowledge Asymmetries

Although general openness toward AI exists, structured competence development remains limited. All internal stakeholders reported informal peer-based learning and individual experimentation with AI tools. While mandatory training related to the EU AI Act was mentioned, practical, workflow-specific AI training was described as insufficient.

As one project manager noted:

"We would benefit from more hands-on examples, not just general discussions, but training tailored to our actual work."

Digital literacy levels also vary across staff. While many employees experiment confidently with AI tools, others remain cautious or uncertain. This variation creates uneven readiness across departments and reinforces the need for structured competence-building measures.

4.4.4.Implementation and Alignment Gaps

A recurring theme concerns the alignment between digital initiatives and stakeholder involvement. While leadership articulated a clear strategic vision for digital transformation, several operational participants expressed limited awareness of the current status of the CRM system or planned AI integrations.

One interviewee remarked:

"From a project manager perspective, we are not really informed about the process yet."

This indicates that readiness is not solely a matter of individual acceptance but also of communication and participatory implementation processes. Digital transformation initiatives appear to be progressing, yet organizational alignment across hierarchical levels possibly remains incomplete.

4.4.5.Cultural Norms and Identity Preservation

Beyond structural factors, readiness is shaped by cultural norms regarding authorship, professional autonomy and evaluative responsibility. QA is described as a human-centered process grounded in expertise, deliberation and trust.

All stakeholders consistently emphasized that any AI integration must preserve this identity. As the managing director articulated:

"The end goal is to make the workflow easier and faster, but the human resource remains our most valuable asset."

This perspective reflects a readiness model rooted in controlled augmentation rather than radical automation. AI integration is considered acceptable insofar as it enhances, rather than displaces, professional roles.

Overall, organizational readiness within FIBAA can be characterized as strategically proactive, operationally conditional and culturally bounded. Openness toward AI is evident across stakeholder groups, yet implementation success depends on maintaining professional judgement authority, improving governance clarity and strengthening structured training mechanisms.

These readiness dynamics provide the empirical foundation for the integrated adoption model and readiness framework presented in the following sections.

4.5. Cross-Case Comparative Analysis

While general openness toward AI integration is observable across stakeholder groups, the analysis reveals meaningful differences in how AI is interpreted, valued and bounded. These differences reflect institutional roles, professional responsibilities and exposure to decision-making authority.

Table 4.1 summarizes the comparative patterns identified across stakeholder categories.

Stakeholder	Current AI Use	Primary	Primary Concern	Overall
Executive Leadership and Division Managers	- Conceptual - strategic	- Strategic positioning, - meta-analysis,	- Governance clarity, - maintaining human authority	Proactive but bounded
Project Managers	- Language refinement	- Document pre-checking,	- Contextual precision,	Pragmatically conditional

F-ACC member and Experts	- Minimal/selective use	- Structured summaries,	- Preservation of evaluative	Protective and cautious
Client - 1	- Intensive internal AI use	- Faster review cycles,	- Transparency of AI involvement	Largely positive
Client - 2	- Moderate familiarity	- Administrative streamlining	- Loss of human interaction,	Cautiously open

Table 1. Comparative patterns across stakeholder Categories

4.5.1.Management Perspective: Strategic Augmentation

The Executive leadership, the division managers and the deputy division managers, frame AI primarily as a strategic development. AI is interpreted as an inevitable technological shift influencing higher education globally. The emphasis lies on maintaining competitiveness and exploring structured analytical potential, such as meta-analysis across QA data.

At the same time, narratives consistently preserve the boundary of human decision authority. AI is positioned as an assistant that enhances workflow efficiency and organizational intelligence, but not as a substitute for expert deliberation.

This perspective reflects proactive readiness combined with normative constraint.

4.5.2.Operational Perspective: Efficiency Under Constraint

Project managers demonstrate the highest degree of practical experimentation with AI tools. Their orientation toward AI is primarily shaped by workload realities. Repetitive document checks, extensive research and report structuring tasks generate openness toward automation.

However, operational stakeholders including some division managers also express strong concern regarding domain specificity. Failed attempts to use generic AI tools for complex comparison tasks reinforce skepticism about AI’s current precision capabilities. Acceptance therefore depends on demonstrable improvements in efficiency without compromising accuracy or increasing supervisory burden.

Operational readiness can thus be characterized as pragmatic and performance-driven.

4.5.3. F-ACC Perspective: Authority Protection

F-ACC commission members as experienced experts also, adopt the most protective stance. Their professional role centers on final evaluative judgement, which they perceive as inherently interpretive and experience-based.

While structured summaries and criterion alignment tools are seen as potentially helpful, the core deliberative function of QA is regarded as purely human and strictly not to be automated. Concerns focus less on administrative efficiency and more on preserving the legitimacy of decision-making.

This orientation establishes the strongest boundary condition within the organization.

4.5.4.Client Perspectives: Efficiency Versus Human Interaction

External clients demonstrate extremely bifurcated perspectives. Some, particularly those already integrating AI extensively within their own institutions, express strong support for AI-supported initial document review and process acceleration. For these stakeholders, AI aligns with expectations of modern administrative efficiency.

Other client emphasized the importance of the human dimension of their accreditation process experience. They value personal communication, direct guidance and the perceived seriousness of a rigorous process. For these stakeholders, automation must not diminish human contact or symbolic legitimacy.

4.5.5.Converging Patterns and Structural Tensions

Despite these differences, several converging patterns emerge:

- No stakeholder group advocates full automation of evaluative judgement.
- AI is broadly acceptable in structured, repetitive, and preparatory tasks.
- Contextual specificity and legal precision are perceived as limiting factors.
- Organizational identity and legitimacy function as moderating variables.

The cross-case comparison reveals that AI acceptance within FIBAA is not binary but role-dependent. Acceptance increases as tasks become more structured and decreases as tasks require interpretive authority or symbolic legitimacy.

These differentiated orientations provide the empirical basis for modeling AI adoption as a dynamic interaction between usefulness, authority boundaries and institutional legitimacy.

4.6. Integrated Model of AI Adoption in Quality Assurance

The empirical findings reveal that AI adoption within QA processes cannot be understood solely through individual acceptance or technological capability. Instead, adoption emerges from the interaction of perceived usefulness, professional judgement authority and institutional legitimacy. To synthesize these dynamics, Figure 1 presents an integrated circular model of AI adoption grounded in the data.

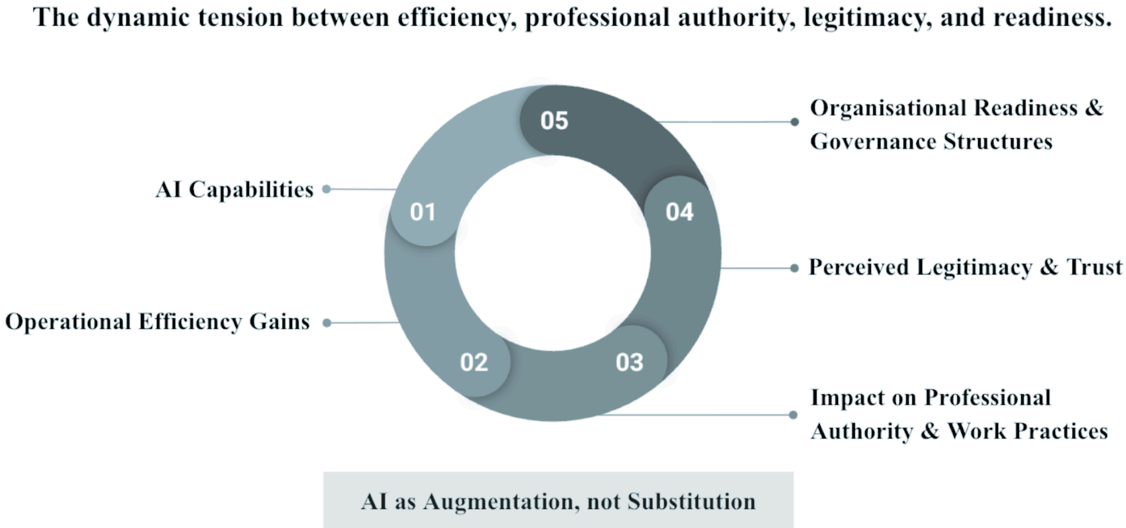

Figure 1. Integrated Circular Model of AI Adoption in Quality Assurance

The model illustrates mutually reinforcing and constraining dimensions. The first dimension reflects perceived operational value. Across stakeholder groups, AI was most readily accepted in structured, repetitive and information-heavy tasks. Document pre-checking, summarization, report structuring and administrative coordination were consistently identified as legitimate areas for automation.

Perceived usefulness increases when AI demonstrably reduces workload without compromising quality. However, usefulness alone does not determine adoption.

The second dimension represents the preservation of professional judgement authority. QA is widely understood as an interpretive, experience-based process requiring contextual understanding and deliberation.

As demonstrated in earlier sections, stakeholders consistently delineate a boundary between procedural assistance and evaluative decision-making. When AI encroaches upon interpretive judgement, acceptance declines sharply. This authority boundary therefore moderates the extent of acceptable automation.

The third dimension concerns legitimacy. QA processes are not only functional assessments but also carry symbolic and reputational value. Duration, deliberation and visible human involvement contribute to perceived credibility.

Acceleration and automation are therefore evaluated not solely in terms of efficiency but also in relation to how they affect perceived seriousness, trustworthiness and institutional identity. Excessive automation risks undermining the symbolic dimension of QA.

These three dimensions interact dynamically rather than linearly. Increased perceived usefulness may support adoption, but only if it does not violate professional authority or reduce institutional legitimacy. Conversely, strong legitimacy concerns may constrain even highly efficient solutions.

AI adoption within FIBAA thus emerges as a negotiated balance between efficiency enhancement, authority preservation and symbolic credibility. Acceptance is highest where AI operates within structured procedural domains, remains transparently supportive, and reinforces rather than destabilizes organizational identity.

4.7. AI Readiness Framework for Quality Assurance Agencies

Building on the integrated adoption model (Figure 1), Figure 2, translates the empirical findings into a four-quadrant AI readiness framework. Rather than presenting readiness as a checklist, the framework conceptualizes readiness as a system of interdependent

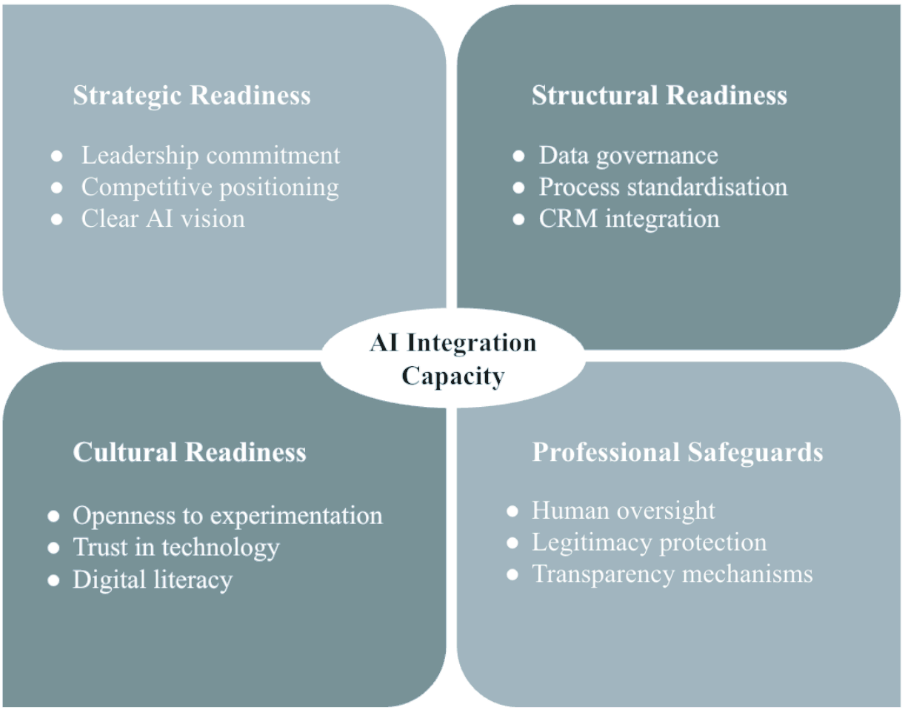

Figure 2. AI Readiness Framework for Quality Assurance Agencies

conditions that must remain aligned for stable AI integration within a QA agency.

The four quadrants Strategic Readiness, Structural Readiness, Cultural Readiness and Professional Safeguards reflect the dominant readiness patterns identified in the data.

Strategic readiness refers to leadership orientation, long-term positioning and recognition of AI as a structural development in higher education governance.

The findings demonstrate that FIBAA's leadership views AI not as a temporary technological trend but as an inevitable development affecting QA markets, institutional expectations and international competitiveness. AI is framed as both opportunity and necessity.

However, this strategic openness is explicitly bounded. AI is positioned as a supportive enhancement mechanism rather than a substitute for evaluative authority. Strategic readiness is therefore proactive but normatively constrained.

Importantly, strategic ambition remains linked to institutional legitimacy. Innovation is acceptable only if it strengthens rather than weakens credibility and trust.

Structural readiness refers to infrastructural capacity, workflow compatibility, governance mechanisms and formal implementation structures.

FIBAA demonstrates relatively high digital maturity through structured project management systems, standardized QA criteria, secure document platforms and the development of a CRM system.

At the same time, current AI use remains dependent on generic tools rather than domain-adapted systems. Formal AI governance mechanisms are still emerging, and role-specific training structures are limited.

Structural readiness can therefore be characterized as foundational but incomplete: infrastructure exists, yet integration mechanisms and formalized governance structures require further development.

Cultural readiness captures shared attitudes, openness to experimentation, and learning dynamics within the organization.

Across interviews, general openness toward automation and AI experimentation was evident. Staff members express curiosity and willingness to explore efficiency gains, particularly for repetitive administrative tasks.

However, cultural acceptance is not uniform. Levels of digital literacy vary, informal peer-learning dominates over structured training and uncertainties remain regarding appropriate AI use cases.

Cultural readiness is therefore positive but uneven. Sustained integration will require systematic competence development and shared understanding of AI's capabilities and limitations.

Professional safeguards refer to the clearly articulated boundaries protecting expert judgement, peer review and final decision-making authority.

Across all stakeholder groups, project managers, management, clients, commission members and experts, one principle remained consistent: AI may assist, but evaluative interpretation and final accreditation decisions must remain human-led.

This boundary does not function as resistance; rather, it stabilizes adoption. By clearly defining what AI should not do, the organization creates a controlled environment for safe integration.

Professional safeguards therefore represent a strength. The clarity of these limits reduces uncertainty and protects institutional legitimacy while enabling structured experimentation.

The Overall AI readiness configuration at FIBAA can therefore be summarized as follows:

- Strong strategic orientation toward AI integration
- Solid structural foundations with emerging governance mechanisms
- Generally positive but uneven cultural alignment
- Clear and robust professional safeguards

These quadrants are interdependent. Strategic ambition without cultural alignment risks fragmentation. Structural investment without professional safeguards may threaten legitimacy. Cultural openness without structural clarity may lead to inconsistent use.

Figure 2, therefore represents readiness as a dynamic balance between strategic direction, structural capacity, cultural acceptance and safeguarded professional authority. Sustainable AI integration within QA agencies requires alignment across all four quadrants.

5. Discussion

The findings suggest that AI integration within QA contexts is neither a purely technological nor a purely organizational issue. Rather, it represents a negotiated transformation shaped by three interdependent dimensions: operational efficiency, professional authority and institutional legitimacy.

First, AI is widely perceived as offering significant operational support. Stakeholders across roles identified repetitive and structurally standardized tasks where AI could reduce workload and improve process speed. These findings indicate a strong perceived usefulness of AI when applied to routine, information-intensive tasks. In this sense, AI is viewed primarily as an infrastructural enhancer rather than a decision-making substitute.

Second, despite this openness to procedural support, there is strong consensus that QA remains fundamentally a human, interpretive process. Evaluation involves contextual judgement, disciplinary expertise and deliberative decision-making that cannot be reduced to rule-based automation. Professional authority, particularly that of expert panels and commissions, is central to the credibility of aQA outcomes. AI is therefore acceptable only insofar as it preserves this authority. Any shift toward automated judgement, risks undermining trust in the Quality seal.

Third, perceptions of AI readiness are closely tied to questions of legitimacy. While stakeholders welcome efficiency improvements, they express concern that excessive acceleration or over-standardization may devalue the perceived seriousness of the procedures. In governance-oriented contexts, duration and procedural rigor contribute symbolically to credibility. This creates a structural tension: AI promises speed, but speed may weaken institutional prestige if not carefully managed.

Together, these findings indicate that AI integration in QA must be framed as controlled augmentation rather than transformation by substitution. Readiness is conditional, not dependent solely on technological infrastructure, but on alignment with institutional identity, regulatory responsibility and professional norms.[75]

[75] Raisch, S. and Krakowski, S. (2021). Artificial Intelligence and Management: the Automation–Augmentation Paradox. *Academy of Management Review*, 46(1), pp.192–210. doi:https://doi.org/10.5465/amr.2018.0072.

AI adoption within QA therefore follows a bounded logic: it is embraced at the level of information processing, cautiously explored at the level of analytical support, and firmly rejected at the level of final evaluative judgement.[76]

This layered acceptance pattern reflects a governance-specific model of digital transformation, where legitimacy constraints moderate technological ambition.[77]

5.1. Theoretical Implications

5.1.1. Reconsidering the Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989)[21] posits that technology adoption is primarily determined by perceived usefulness and perceived ease of use. The findings of this study partially support this logic.

Across operational roles, perceived usefulness clearly influences acceptance. Project managers expressed openness toward AI when it supported them in their operational work. In these structured, task-oriented domains, AI adoption aligns closely with TAM's central assumption: technologies are embraced when they demonstrably enhance performance efficiency.

However, the findings also indicate that usefulness alone does not determine acceptance. Even where AI was perceived as functionally beneficial, such as in accelerating report drafting or initial document checks, stakeholders imposed normative boundaries related to professional authority and institutional credibility. F-ACC members, in particular, rejected any form of AI involvement that could encroach upon evaluative judgement, regardless of potential efficiency gains.

This reveals a structural limitation of TAM in governance settings. While perceived usefulness explains adoption in routine procedural tasks, it does not account for the symbolic and authority-based dimensions that shape acceptance in evaluative institutions. In QA contexts, adoption is moderated not only by utility, but by compatibility with professional identity and decision-making legitimacy.

Furthermore, perceived ease of use another central TAM variable was rarely mentioned explicitly by participants. Instead, the decisive factor was contextual appropriateness. AI

[76] Faraj, Pachidi and Sayegh (2018)

[77] Neumann, Guirguis and Steiner (2024)

tools were evaluated not in terms of simplicity, but in terms of whether they "fit" the nature of the QA work. When AI outputs lacked contextual precision or failed to grasp domain-specific nuances, acceptance declined, even if the interface itself was user-friendly.

The findings therefore suggest that TAM remains relevant but incomplete for understanding AI adoption in QA agencies. Perceived usefulness explains conditional openness at the operational level, yet authority preservation and legitimacy considerations introduce moderating constraints beyond TAM's original scope.

In governance-based organizations, technology acceptance appears to follow a layered structure: *usefulness enables experimentation, but institutional boundaries determine integration.*

5.1.2. AI Adoption as a Sociotechnical Reconfiguration

The findings of this study strongly align with the core premises of sociotechnical systems theory, which emphasizes the interdependence between technological infrastructures and social structures. Rather than representing a purely technical enhancement, AI integration within QA processes emerges as a reconfiguration of the relationship between digital systems, professional roles and institutional norms.

Sociotechnical systems theory argues that technological change cannot be successfully implemented without parallel adaptation in social arrangements, including work practices, authority structures and cultural expectations.[78] The empirical findings provide clear evidence of this dynamic. While FIBAA possesses relatively mature digital infrastructure, readiness for AI integration is moderated by professional identity and decision authority boundaries. This demonstrates that technological capability alone is insufficient for transformation.

In particular, the preservation of professional judgement authority reflects what sociotechnical theory conceptualizes as the integrity of the social subsystem. Participants consistently positioned AI as acceptable only when it operates within structured procedural domains and does not intrude upon evaluative authority. This suggests that AI must be aligned with the social logic of QA rather than disrupt it.

[78] Sarker et al. (2019)

Moreover, legitimacy concerns previously identified, highlighted an additional sociotechnical layer: the institutional environment. QA agencies operate within regulatory and symbolic frameworks where trust and credibility are central. If AI integration were perceived as diminishing procedural seriousness or replacing expert deliberation, the social subsystem could destabilize, regardless of technical efficiency gains.

The findings therefore support a sociotechnical interpretation of AI adoption as a process of negotiated alignment. Technical systems may optimize information processing, but they must remain compatible with professional norms and governance expectations. AI integration in QA is thus best understood not as automation of work, but as recalibration of human-technology interaction within a rule-bound evaluative ecosystem.

In this context, the integrated adoption model presented in Figure 1 can be interpreted as a sociotechnical balancing mechanism. Perceived usefulness reflects the technical subsystem, professional judgement authority reflects the social subsystem and institutional legitimacy represents the broader institutional environment within which both operate.

The study therefore extends sociotechnical theory into the domain of QA governance by demonstrating that AI adoption is constrained not primarily by technological readiness, but by alignment with institutionalized authority structures.

5.1.3. AI Integration as Controlled Digital Transformation

The findings also contribute to the literature on digital transformation and organizational change. Digital transformation is commonly conceptualized as a process through which organizations integrate digital technologies to fundamentally reshape processes, structures and value creation mechanisms.[79] However, the empirical evidence from this study suggests that in governance-oriented contexts such as QA, transformation unfolds as controlled augmentation rather than structural disruption.

Participants did not frame AI as a radical reconfiguration of quality assurance processes. Instead, they articulated a preference for incremental integration targeting repetitive and information-intensive tasks. This cautious approach reflects what digital transformation

---

[79] Vial (2019)

literature describes as context-dependent adaptation rather than universal technological substitution.[80] In highly regulated and legitimacy-sensitive environments, transformation must be aligned with institutional purpose and stakeholder trust.

Furthermore, research on AI implementation in organizational settings emphasizes that readiness is multidimensional, encompassing strategic alignment, digital capabilities, governance clarity and human competencies.[81] The readiness framework developed in Chapter 4 reflects precisely this multidimensional structure. While FIBAA demonstrates strategic awareness and digital infrastructure maturity, organizational alignment and structured competence development remain uneven. This indicates that AI integration is constrained by the organization's capacity to coordinate change across hierarchical and functional boundaries.

Importantly, the data also reveal an implementation alignment gap. Leadership expresses proactive commitment to AI exploration, yet some operational stakeholders report limited involvement in digital initiative design. Change management literature consistently highlights the importance of participatory implementation and communication in reducing resistance and improving adoption outcomes.[82] In this case, resistance is not overt; rather, conditional acceptance depends on perceived clarity of purpose and practical benefit.

The findings therefore suggest that AI adoption in QA agencies should not be conceptualized as digital transformation in the disruptive sense often associated with platform economies or market restructuring. Instead, it represents institutional recalibration: a process of embedding digital intelligence within established professional and regulatory frameworks.

Transformation, in this context, is not about replacing human expertise but about redesigning workflows in ways that preserve institutional identity while enhancing operational resilience. This interpretation extends digital transformation theory by demonstrating that in evaluative governance institutions, legitimacy constraints shape the pace and scope of technological change.

---

[80] Verhoef et al. (2021)

[81] Jöhnk, Weißert and Wyrtki (2021)

[82] Vial (2019)

5.2. Operationalizing AI Integration in Quality Assurance

Based on the empirical findings and theoretical interpretation[83], this section proposes a structured pathway for operationalizing AI within QA agencies. The framework does not advocate radical automation, but phased and controlled augmentation.

Two complementary models are presented:

(1) a phased AI integration pathway and

(2) a future AI-supported QA workflow.

5.2.1. Phased AI Integration Pathway

The phased model conceptualizes AI integration as a gradual progression from foundational alignment to strategic intelligence deployment.

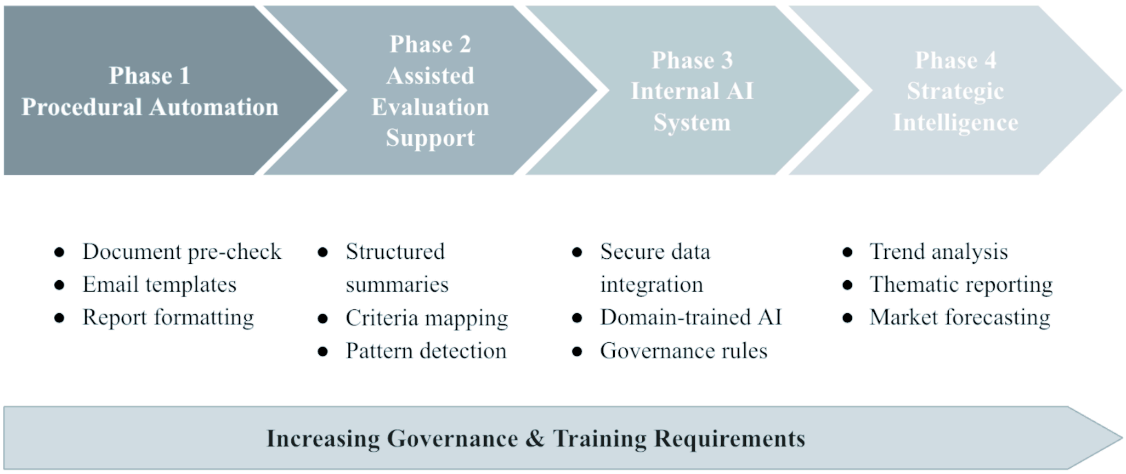

Figure 3. Phased AI Integration Pathway for Quality Assurance Agencies

Phase 1: Foundational Alignment and Governance Framing

The first phase involves establishing conceptual clarity and institutional boundaries. The findings show that professional judgement authority and legitimacy concerns moderate acceptance. This phase addresses sociotechnical alignment by ensuring that technological development does not outpace normative integration. Therefore, AI integration must begin with:

- Clear articulation of augmentation logic
- Definition of acceptable use cases

[83] Jöhnk, Weißert and Wyrtki (2021); Raisch and Krakowski (2021); Wirtz, Weyerer and Geyer (2019)

- Development of internal AI governance guidelines
- Communication of scope limitations to staff and stakeholders
- Targeted competence-building initiatives

Phase 2: Controlled Procedural Automation

Once alignment is established, AI can be introduced in structured, low-risk procedural domains. The empirical data indicate high acceptance in repetitive and information-intensive tasks. These applications align closely with perceived usefulness and reduce administrative burden without encroaching on evaluative authority. Suitable entry points include:

- Automated document completeness checks
- Structured report templates and consistency validation
- Language refinement support
- Expert FAQ chat interfaces
- Email prioritization systems

Phase 3: Internal AI Infrastructure Development

Following successful procedural integration, agencies may develop secure, domain-specific AI systems. Participants expressed interest in internal models trained on historical reports, quality criteria and decision precedents. By transitioning from generic large language models to context-trained systems, agencies can address precision and data governance concerns identified in the findings. This phase would involve:

- Development of a secure, GDPR-compliant internal AI environment
- Controlled training using anonymized QA data
- Role-based AI interfaces (e.g., project manager, commission, expert panel)
- Monitoring and validation mechanisms

Phase 4: Strategic Analytical Intelligence

In the final phase, AI evolves from procedural support to institutional intelligence. This phase supports strategic planning and policy development without altering the locus of evaluative authority. This includes:

- Meta-analysis across QA reports

- Trend detection in conditions and recommendations
- Comparative institutional development tracking
- Predictive workload modelling

5.2.2. AI-Supported QA Workflow Model

Complementing the phased pathway, Figure 4 illustrates how AI could be embedded within the QA workflow while preserving human decision-making authority.

The model reflects the principle of "AI as structured assistant."

Figure 4. AI-Supported QA Workflow Model

Step 1: Application Submission

AI functions: automated completeness verification, identification of missing documentation and preliminary structural mapping

Human role: validation of AI flags and initial contextual assessment

Step 2: Pre-Review and Expert Preparation

AI functions: summarization of self-evaluation reports, mapping of criteria coverage, highlighting potential inconsistencies and preparation of structured question clusters

Human role: interpretive evaluation and selection of discussion priorities

Step 3: Site Visit and Deliberation

AI functions: real-time documentation support and structured note summarization

Human role: conduct interviews, evaluate responses and exercise professional judgement

Step 4: Report Drafting

AI functions: structural alignment with criteria, consistency checks across sections and detection of contradictory statements

Human role: draft evaluative reasoning and formulate conditions and recommendations

Step 5: Commission Review

AI functions: identification of decision inconsistencies, historical comparison with precedent cases and structured summary generation

Human role: deliberate and issue final decision,

Across all phases and workflow stages, one principle remains constant: AI supports information processing, it is not an evaluative authority.

This boundary condition reflects the empirical finding that legitimacy and trust are inseparable from human judgement in QA processes.

Operationalizing AI in this structured manner enables agencies to improve efficiency without undermining credibility, reduce administrative burden while preserving expertise, strengthen strategic intelligence capacity and maintain competitive positioning in international markets

By integrating AI incrementally and transparently, QA agencies can reconcile technological advancement with institutional identity.

5.3. Contributions of the Study

Empirically, the study provides one of the first in-depth qualitative analyses of AI integration within an QA agency context. While much existing research on AI in higher education focuses on teaching, learning analytics, or administrative automation, considerably less attention has been paid to governance-oriented institutions responsible for external QA.

By examining stakeholder perceptions across management, operational staff, commission members, experts and clients, the study reveals that AI adoption in QA is structured by role-dependent interpretations. Acceptance varies systematically according to task type, authority position and proximity to evaluative decision-making.

The findings demonstrate that AI is most readily accepted in structured procedural domains and least accepted where interpretive authority and legitimacy are at stake.

This layered acceptance pattern provides empirical nuance to existing debates on AI adoption in higher education governance.

Theoretically, the study refines and extends existing models of technology adoption in institutional contexts.

First, while the Technology Acceptance Model[84] explains operational acceptance through perceived usefulness, the findings demonstrate that usefulness alone is insufficient in governance environments. Professional judgement authority and institutional legitimacy function as moderating constraints beyond TAM's original scope.

Second, the study empirically substantiates sociotechnical systems theory[85] by demonstrating that AI adoption requires alignment between technical systems and professional authority structures. Technological optimization does not automatically translate into institutional integration.

Third, the research extends digital transformation literature[86] by showing that transformation within evaluative governance organizations is characterized by controlled augmentation rather than disruptive restructuring. In QA contexts, legitimacy constraints shape the pace and scope of change.

Practically, the study offers a structured pathway for AI integration tailored to QA agencies. The phased AI integration model (Figure 3) and the AI-supported workflow model (Figure 4) provide actionable guidance grounded in empirical evidence rather than speculative technological enthusiasm.

The research suggests that agencies should prioritize procedural automation, develop secure internal AI infrastructures, and implement structured training frameworks before expanding toward strategic analytical applications.

By framing AI as augmentative rather than substitutive, agencies can enhance operational efficiency while preserving professional authority and institutional trust.

[84] Davis (1989); Venkatesh and Davis (2000)

[85] Sarker et al. (2019)

[86] Verhoef et al. (2021); Vial (2019)

5.4. Limitations

While this study provides in-depth insights into AI integration within a QA agency, several limitations must be acknowledged.

First, the research is based on a single-case study. Although FIBAA represents a mature and internationally active QA agency, findings are context-bound and cannot be statistically generalized to all QA organizations. The purpose of the study, however, was analytical rather than statistical generalization. Future research could conduct comparative multi-case analyses across QA agencies in different national or regulatory environments to examine how institutional context shapes AI readiness.

Second, the study focuses on stakeholder perceptions and anticipated integration rather than on longitudinal observation of fully implemented AI systems. As such, the findings capture expectations, boundary conditions and readiness dynamics rather than measured performance outcomes. Future research could investigate the operational impact of implemented AI systems on accreditation timelines, workload distribution and decision consistency.

Lastly, while the study included multiple stakeholder groups, the sample size remains limited. Quantitative surveys across broader stakeholder populations could complement qualitative findings and assess the prevalence of identified patterns, such as the acceleration vs. legitimacy tension or authenticity concerns.

5.5. Future Outlook

The rapid advancement of artificial intelligence may alter some of the feasibility boundaries identified in this study. As AI systems become more capable of processing complex documentation, synthesizing information across large datasets and supporting analytical reasoning, their potential role in higher education governance may expand beyond the supportive functions currently considered acceptable within QA agencies. Longitudinal research tracking AI adoption over time would therefore be particularly valuable for understanding how stakeholder perceptions, institutional norms and regulatory expectations evolve as these technologies mature.

Recent scholarship has begun to envision more transformative forms of AI-enabled QA. For example, Nuruddeen (2025)[87] proposes the concept of "intelligent assurance," in which AI systems support continuous monitoring of institutional performance, automated analysis of quality indicators and real-time evaluation of educational outcomes. Such models suggest a shift from periodic QA cycles toward more dynamic and data-driven forms of oversight.

While these developments highlight the long-term potential of AI in higher education governance, their implementation within European QA systems would likely require significant institutional adaptation. Current QA models within the European Higher Education Area remain strongly anchored in peer review, professional judgement and procedural legitimacy as articulated in the European Standards and Guidelines for Quality Assurance (ESG). As a result, the transition toward AI-supported continuous assurance models would raise important questions concerning accountability, explainability and the preservation of expert authority in evaluative decision-making.

Future research should therefore explore how emerging AI capabilities interact with regulatory frameworks, governance structures and professional practices within QA agencies. Particular attention may be given to the ethical and regulatory implications of domain-trained AI systems in QA contexts, including issues of data governance, algorithmic transparency and explainability under evolving regulatory regimes such as the EU Artificial Intelligence Act.

Despite these uncertainties, the present study provides a structured foundation for understanding AI adoption in governance-oriented higher education institutions. By identifying both operational opportunities and institutional constraints, the findings offer a conceptual basis for future empirical research on how QA systems may evolve as digital technologies continue to reshape higher education governance.

5.6. Conclusion

Artificial intelligence is often framed as a disruptive force capable of fundamentally transforming organizational processes. However, the findings of this study suggest that within governance-oriented institutions such as QA agencies, transformation unfolds

[87] Nuruddeen, U.A. (2025). Intelligent Assurance: Leveraging AI for Enhanced Quality in Higher Education. In: P.A. Okebukola, ed., *AI and Ethics, Academic Integrity and the Future of Quality Assurance in Higher Education*. Sterling Publishers, pp.441–447.

differently. Rather than replacing professional expertise, AI integration emerges as a negotiated process shaped by institutional norms, authority structures and legitimacy requirements.

In the context of QA, the central question is not whether AI can accelerate procedures or optimize information processing. The more decisive question concerns the conditions under which technological augmentation can coexist with professional judgement and institutional trust. QA operates within a framework of credibility, accountability and interpretive authority. These characteristics do not resist digitalization, they define its acceptable scope.

The analysis demonstrates that AI is most viable when positioned as structured assistance within clearly bounded domains. When aligned with organizational identity and embedded within transparent governance frameworks, AI can enhance efficiency without undermining evaluative integrity. When framed as substitution for expert deliberation, however, it risks destabilizing the symbolic foundations upon which QA legitimacy depends.

The future of AI in QA therefore lies not in automation of judgement, but in augmentation of institutional intelligence. Agencies that navigate this balance successfully may strengthen both operational resilience and strategic insight, while preserving the human-centered nature of evaluation.

In this sense, AI integration within QA is not a technological question alone. It is an institutional design challenge, one that requires careful alignment between digital capability and professional responsibility.

While the study remains context-bound to a single QA agency, the identified dynamics illustrate broader institutional tensions relevant to governance-oriented organizations navigating AI integration.

VI. References

Ahsan, K., Akbar, S., Kam, B. and Abdulrahman, M.D.-A. (2023). Implementation of micro-credentials in higher education: A systematic literature review. *Education and Information Technologies*, 28, pp.13505–13540. doi:https://doi.org/10.1007/s10639-023-11739-z.

Beerkens, M. (2015). Quality Assurance in the Political context: in the Midst of Different Expectations and Conflicting Goals. *Quality in Higher Education*, 21(3), pp.231–250. doi:https://doi.org/10.1080/13538322.2015.1111004.

Berente, N., Gu, B., Recker, J. and Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly*, 45(3), pp.1433–1450. doi:https://doi.org/10.25300/MISQ/2021/16274.

Bowen, G.A. (2009). Document Analysis as a Qualitative Research Method. *Qualitative Research Journal*, 9(2), pp.27–40. doi:https://doi.org/10.3316/QRJ0902027.

Cardoso, S., Rosa, M.J. and Stensaker, B. (2015). Why is quality in higher education not achieved? The view of academics. *Assessment & Evaluation in Higher Education*, 41(6), pp.950–965. doi:https://doi.org/10.1080/02602938.2015.1052775.

Collins, C., Dennehy, D., Conboy, K. and Mikalef, P. (2021). Artificial Intelligence in Information Systems research: a Systematic Literature Review and Research Agenda. *International Journal of Information Management*, 60(102383). doi:https://doi.org/10.1016/j.ijinfomgt.2021.102383.

Council of the European Union (2022). *A European approach to micro-credentials for lifelong learning and employability*. [online] Official Journal of the European Union. Available at: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32022H0627.

Davis, F.D. (1989). Perceived usefulness, Perceived Ease of use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), pp.319–340. doi:https://doi.org/10.2307/249008.

Dellermann, D., Ebel, P., Söllner, M. and Leimeister, J.M. (2019). Hybrid Intelligence. *Business & Information Systems Engineering*, 61, pp.637–643. doi:https://doi.org/10.1007/s12599-019-00595-2.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P.V., Janssen, M., Jones, P., Kar, A.K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B. and Medaglia, R. (2021). Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging challenges, opportunities, and Agenda for research, Practice and Policy. *International Journal of Information Management*, 57, p.101994. doi:https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

ENQA (2015). *Standards and Guidelines for Quality Assurance in the European Higher Education Area ESG*. [online] Available at: https://www.enqa.eu/wp-content/uploads/2015/11/ESG_2015.pdf.

European Higher Education Area (EHEA) (2024). Tirana Communiqué. [online] Available at: https://ehea.info/Immagini/Tirana-Communique.pdf.

European Parliament, Council of the European Union (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. [online] Available at: http://data.europa.eu/eli/reg/2024/1689/oj.

Faraj, S., Pachidi, S. and Sayegh, K. (2018). Working and Organizing in the Age of the Learning Algorithm. *Information and Organization*, 28(1), pp.62–70. doi:https://doi.org/10.1016/j.infoandorg.2018.02.005.

Freeman, R.E. (1984). *Strategic Management: a Stakeholder Approach*. Boston: Pitman.

Fusch, P., Fusch, G. and Ness, L. (2018). Denzin's Paradigm Shift: Revisiting Triangulation in Qualitative Research. *Journal of Social Change*, 10(1), pp.19–32. doi:https://doi.org/10.5590/JOSC.2018.10.1.02.

Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013). Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology. *Organizational Research Methods*, 16(1), pp.15–31. doi:https://doi.org/10.1177/1094428112452151.

Glaser, B.G. and Strauss, A.L. (1967). *The Discovery of Grounded Theory*. Transaction Publishers.

Harvey, L. and Williams, J. (2010). Fifteen Years ofQuality in Higher Education. *Quality in Higher Education*, 16(1), pp.3–36. doi:https://doi.org/10.1080/13538321003679457.

Holmstrom, J. (2021). From AI to digital transformation: The AI readiness framework. *Business Horizons*, 65(3), pp.329–339. doi:https://doi.org/10.1016/j.bushor.2021.03.006.

Jöhnk, J., Weißert, M. and Wyrtki, K. (2021). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, 63, pp.5–20. doi:https://doi.org/10.1007/s12599-020-00676-7.

Kak , A. and West, Dr.S.M. (2023). *Confronting tech power 2023 Landscape*. [online] AI Now Institute. Available at: https://ainowinstitute.org/2023-landscape.

Karran, A.J., Charland, P., Trempe-Martineau, J., Ortiz de Guinea Lopez de Arana, A., Lesage, A.-M., Sénécal, S. and Léger, P.-M. (2025). Multi-stakeholder Perspective on

Responsible Artificial Intelligence and Acceptability in Education. *npj Science of Learning*, 10(1). doi:https://doi.org/10.1038/s41539-025-00333-2.

Kvale, S. and Brinkmann, S. (2015). *InterViews: Learning the Craft of Qualitative Research Interviewing*. 3rd ed. SAGE Publications Ltd.

Makridakis, S. (2017). The Forthcoming Artificial Intelligence (AI) revolution: Its Impact on Society and Firms. *Futures*, 90(90), pp.46–60. doi:https://doi.org/10.1016/j.futures.2017.03.006.

Manatos, M.J., Rosa, M.J. and Sarrico, C.S. (2015). The importance and degree of implementation of the European standards and guidelines for internal quality assurance in universities: the views of Portuguese academics. *Tertiary Education and Management*, 21(3), pp.245–261. doi:https://doi.org/10.1080/13583883.2015.1061587.

Mergel, I., Dickinson, H., Stenvall, J. and Gascó, M. (2023). Implementing AI in the public sector. *Public Management Review*, pp.1–14. doi:https://doi.org/10.1080/14719037.2023.2231950.

Mergel, I., Edelmann, N. and Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, 36(4), p.101385. doi:https://doi.org/10.1016/j.giq.2019.06.002.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, 30(2), pp.272–298. doi:https://doi.org/10.1111/1467-8551.12343.

Myers, M.D. (2009). *Qualitative Research in Business & Management*. 2nd ed. SAGE Publications Ltd. doi:https://doi.org/10.4135/9781036208417.

Neumann, O., Guirguis, K. and Steiner, R. (2024). Exploring Artificial Intelligence Adoption in Public organizations: a Comparative Case Study. *Public Management Review*, 26(1), pp.114–141. doi:https://doi.org/10.1080/14719037.2022.2048685.

Nuruddeen, U.A. (2025). Intelligent Assurance: Leveraging AI for Enhanced Quality in Higher Education. In: P.A. Okebukola, ed., *AI and Ethics, Academic Integrity and the Future of Quality Assurance in Higher Education*. Sterling Publishers, pp.441–447.

OECD (2023). Quality and value of micro-credentials in higher education. *OECD Publishing*, 66. doi:https://doi.org/10.1787/9c4b7b68-en.

Rahman, M.S., Bag, S., Gupta, S. and Sivarajah, U. (2023). Technology readiness of B2B firms and AI-based customer relationship management capability for enhancing social sustainability performance. *Journal of Business Research*, 156, p.113525. doi:https://doi.org/10.1016/j.jbusres.2022.113525.

Raisch, S. and Krakowski, S. (2021). Artificial Intelligence and Management: the Automation–Augmentation Paradox. *Academy of Management Review*, 46(1), pp.192–210. doi:https://doi.org/10.5465/amr.2018.0072.

Sarker, S., Chatterjee, S., Xiao, X. and Elbanna, A. (2019). The Sociotechnical Axis of Cohesion for the IS Discipline: Its Historical Legacy and Its Continued Relevance. *MIS Quarterly*, 43(3), pp.695–719. doi:https://doi.org/10.25300/misq/2019/13747.

Stahl, B.C., Andreou, A., Brey, P., Hatzakis, T., Kirichenko, A., Macnish, K., Laulhé Shaelou, S., Patel, A., Ryan, M. and Wright, D. (2021). Artificial intelligence for human flourishing – Beyond principles for machine learning. *Journal of Business Research*, 124, pp.374–388. doi:https://doi.org/10.1016/j.jbusres.2020.11.030.

Stensaker, B. (2007). Quality as Fashion: Exploring the Translation of a Management Idea into Higher Education. In: D.F. Westerheijden, B. Stensaker and M.J. Rosa PhD, eds., *Quality Assurance in Higher Education*. Springer, Dordrecht, pp.99–118. doi:https://doi.org/10.1007/978-1-4020-6012-0_4.

Stensaker, B. and Harvey, L. eds., (2011). *Accountability in Higher Education Global Perspectives on Trust and Power*. Routledge, pp.1–22.

Strauss, A. and Corbin, J. (2008). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*. 3rd ed. *SAGE Publications*. doi:https://doi.org/10.4135/9781452230153.

Uren, V. and Edwards, J.S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68(1), p.102588. doi:https://doi.org/10.1016/j.ijinfomgt.2022.102588.

Venkatesh, V. and Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), pp.186–204. doi:https://doi.org/10.1287/mnsc.46.2.186.11926.

Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N. and Haenlein, M. (2021). Digital transformation: a Multidisciplinary Reflection and Research Agenda. *Journal of Business Research*, 122, pp.889–901. doi:https://doi.org/10.1016/j.jbusres.2019.09.022.

Vial, G. (2019). Understanding Digital transformation: a Review and a Research Agenda. *The Journal of Strategic Information Systems*, 28(2), pp.118–144. doi:https://doi.org/10.1016/j.jsis.2019.01.003.

Warren, S.J., Boston Vogt, E., Tincher, B. and Yang, J. (2025). Enhancing quality assurance through strategic artificial intelligence integration: a framework for higher education digital transformation. *Quality Assurance in Education*, 34(2). doi:https://doi.org/10.1108/qae-09-2024-0183.

Wirtz, B.W., Weyerer, J.C. and Geyer, C. (2019). Artificial Intelligence and the Public Sector—Applications and Challenges. *International Journal of Public Administration*, 42(7), pp.596–615. doi:https://doi.org/10.1080/01900692.2018.1498103.

Yin, R.K. (2017). *Case Study Research and Applications: Design and Methods*. 6th ed. Thousand Oaks, California: Sage Publications.

Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019). Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where are the Educators? *International Journal of Educational Technology in Higher Education*, 16(39). doi:https://doi.org/10.1186/s41239-019-0171-0.

VII.Appendices

A. Interview Guides

Each guide follows a semi-structured format, allowing flexibility to explore emerging themes while maintaining consistency across interviews for qualitative analysis.

Interview Guide -1

Target Group:
FIBAA operational staff, division managers, deputy division managers and project managers involved in QA activities.

Objective:
To understand internal perspectives on AI adoption, identify workflow challenges, and assess readiness for digital transformation.

Section 1: Introduction and Context

1. Can you describe your current role and responsibilities within FIBAA?
2. How do digital tools currently support your daily work and communication?

Section 2: Current Processes and Pain Points

3. What are the main steps in your current QA or accreditation processes?
    - Which steps are most time-consuming or repetitive?
    - Are there recurring challenges or bottlenecks?
4. How is data or documentation currently managed and reviewed?

Section 3: Experience and Perception of AI

5. How familiar are you with Artificial Intelligence and its applications in your professional context?
6. Where do you think AI could support FIBAA's work?
    - For example, in document review, report generation, or data analysis?
7. What potential benefits do you see from AI integration (e.g., time efficiency, improved accuracy, consistency)?
8. What risks or concerns do you associate with AI (e.g., bias, transparency, data privacy)?

Section 4: Readiness for Digital and AI Transformation

9. How would you describe FIBAA's current level of digitalization?
10. How open do you think employees and management are toward AI-based tools?
    - What factors might build trust and acceptance?
    - What training or support would be necessary for successful adoption?
11. What internal or external resources could support AI implementation within FIBAA?

Section 5: Future Vision and Implementation

12. If you could improve or automate any part of your work with AI, what would be your top priorities?
13. What would an ideal AI-assisted process look like to you?
14. How can AI be integrated without compromising FIBAA's standards of quality and fairness?

Section 6: Closing

15. Is there anything else you would like to share regarding digitalization or AI integration at FIBAA?

Interview Guide -2

Target Group:
Experts, Clients, F-ACC member and executive leadership.

Objective:
To understand perceptions of FIBAA's processes, explore expectations toward digitalization, and assess the perceived value and concerns regarding AI-driven QA.

Section 1: Introduction and Context

1. Could you describe your relationship or collaboration with FIBAA?
2. Which parts of the accreditation or evaluation process do you interact with most?

Section 2: Perceptions of FIBAA's Current Processes

3. How would you describe your experience with FIBAA's current processes?
    - What works well?
    - What could be improved?
4. How do you perceive FIBAA's efficiency and transparency compared to other agencies or institutions?

Section 3: Awareness and Attitude toward AI in QA

5. What is your understanding of how AI could support higher education QA?
6. Where do you think AI could add value to FIBAA's work?
    - For example, in data evaluation, document checking, communication, or monitoring outcomes?
7. What concerns might you have about AI use in such processes (e.g., human judgment, bias, data security)?

Section 4: Expectations and Collaboration Opportunities

8. From your perspective, what AI or digital tools could make collaboration with FIBAA more efficient?
9. How could AI improve transparency, feedback, or communication between FIBAA and institutions?
10. How can FIBAA ensure accountability and trust when integrating AI into its processes?

Section 5: Future Outlook

11. How do you envision the role of AI in accreditation and QA over the next 5–10 years?
12. What would you recommend FIBAA consider when developing its AI and digitalization strategy?
13. Are there good practices or models from other organizations that could serve as inspiration?

Section 6: Closing

14. Is there anything else you would like to add regarding AI in QA or your experience with FIBAA?

B. Axial Categories

Axial Category	Description	Key Stakeholders
AI as Procedural Infrastructure	AI is accepted for structured administrative support tasks such as summarizing documents, checking requirements, scheduling, and information retrieval.	Project Managers, Commission Members, Leadership
Epistemic Sovereignty Preservation	Final accreditation decisions must remain human because evaluation requires expert interpretation and professional judgement.	Commission Members, Project Managers
Acceleration vs Legitimacy Paradox	Faster processes increase efficiency but may reduce perceived legitimacy and prestige of accreditation procedures.	Commission, Leadership
Authenticity Devaluation Anxiety	AI-generated text is often perceived as less authentic or lower effort even when technically correct.	Project Managers, Commission Members
Contextual Precision Requirement	AI must understand complex accreditation criteria and contextual institutional differences to be trusted.	Project Managers, Commission
Implementation vs. Alignment Gap	Digital tools exist but are not fully aligned with governance, training, or communication structures.	Project Managers, Leadership
AI-Induced Evaluative Escalation	Universities may use AI to optimize accreditation submissions, creating more complex evaluation processes.	Project Managers, Commission
Strategic Digital Necessity	Digital automation is seen as necessary for maintaining competitiveness and operational efficiency in the accreditation market.	Leadership, Project Managers

Axial Category	Representative Open Codes
AI as Procedural Infrastructure	AI-assisted document summaries; automatic document checks; scheduling support; information retrieval; structured report support
Epistemic Sovereignty Preservation	final responsibility remains human; expert judgement required; accreditation decisions cannot be automated
Acceleration vs. Legitimacy Paradox	process too slow; need efficiency; fast processes reduce perceived prestige; time required for legitimacy

Authenticity Devaluation Anxiety	AI text recognizable; AI content perceived as lower effort; preference for self-written reports
Contextual Precision Requirement	AI lacks domain understanding; accreditation work is niche; need domain-specific AI training
Implementation vs. Alignment Gap	unclear CRM implementation; lack of governance clarity; tool proliferation; informal AI learning
AI-Induced Evaluative Escalation	clients using AI to prepare reports; optimized submissions; evaluators must verify more carefully
Strategic Digital Necessity	automation required for competitiveness; cost pressure; international market expansion

Axial Category	**Phenomenon**	**Causal Conditions**	**Actions/ Interactions**	**Consequences**
AI as Procedural Infrastructure	Use of AI for structured administrative support	High document workload	AI used for summarizing and compliance checking	Improved operational efficiency
Epistemic Sovereignty Preservation	Protection of human decision authority	Accreditation requires expert judgement	Maintain human oversight	Controlled AI integration
Acceleration vs. Legitimacy Paradox	Tension between efficiency and symbolic value	Competitive market pressure	Partial automation	Hybrid accreditation processes
Authenticity Devaluation Anxiety	Concern about authenticity of AI-generated content	Detectable AI writing patterns	Human editing of AI output	Continued human authorship norm
Contextual Precision Requirement	Need for domain-specific AI capabilities	Complex accreditation criteria	Limit AI use to structured tasks	Slow adoption of advanced automation
Implementation vs. Alignment Gap	Organizational misalignment in digitalization	Rapid introduction of tools	Informal experimentation and learning	Uneven digital readiness
AI-Induced Evaluative Escalation	Increasing AI use by universities	Easy access to AI writing tools	More verification by evaluators	Higher evaluation complexity
Strategic Digital Necessity	Digital transformation as competitive requirement	Cost pressure and international competition	Strategic investment in automation	Long-term organizational transformation

TAM Model

Axial Category	TAM Construct	Explanation
AI as Procedural Infrastructure	Perceived Usefulness	Stakeholders see clear efficiency gains in structured support tasks (summaries, checks, scheduling).
Contextual Precision Requirement	Perceived Usefulness + Perceived Risk	AI is useful only if domain-specific; general AI lowers usefulness due to precision gaps.
Epistemic Sovereignty Preservation	Perceived Risk	Fear of authority displacement reduces acceptance.
Authenticity Devaluation Anxiety	Perceived Risk + Compatibility	AI conflicts with norms of authorship and effort signalling.
Implementation vs. Alignment Gap	Perceived Ease of Use	Lack of training and unclear governance reduces usability.
Acceleration vs. Legitimacy Paradox	Perceived Usefulness vs Norm Compatibility	Speed useful operationally but conflicts with institutional legitimacy norms.
AI-Induced Evaluative Escalation	Perceived Risk	Risk of inflated submissions increases verification burden.
Strategic Digital Necessity	External Pressure (Extended TAM)	Competitive environment drives intention to adopt.

Socio-Technical Systems Theory

Axial Category	Technical Dimension	Social Dimension	Alignment Issue
AI as Procedural Infrastructure	Automation tools	Workflow routines	Strong alignment when limited to structured tasks.
Epistemic Sovereignty Preservation	Decision-support systems	Professional identity	Misalignment if AI threatens judgement authority.
Acceleration vs. Legitimacy Paradox	Process automation	Institutional symbolism	Speed disrupts ritual legitimacy structure.
Authenticity Devaluation Anxiety	AI text generation	Cultural norms of effort	Machine fluency conflicts with authenticity norms.
Contextual Precision Requirement	General LLMs	Domain expertise	Need for domain-specific technical adaptation.
Implementation vs. Alignment Gap	CRM, Copilot, AI tools	Training, governance, communication	Weak alignment causing fragmented adoption.
AI-Induced Evaluative Escalation	AI-assisted submissions	Evaluator verification norms	New dynamic increases complexity.
Strategic Digital Necessity	Digital transformation	Market competition	Pressure pushes technical adoption ahead of cultural readiness.

Change Management - Sense-making theory

Axial Category	Change Variable	Diagnosis
Strategic Digital Necessity	Sense of Urgency	Strong at leadership level; weaker operationally.
Implementation vs. Alignment Gap	Communication & Participation	CRM rollout lacks broad inclusion.
Contextual Precision Requirement	Competence Development	Need for targeted AI skill development.
Authenticity Devaluation Anxiety	Emotional Resistance	Symbolic threat to professional identity.
Epistemic Sovereignty Preservation	Identity Protection	Core professional boundaries must be safeguarded.
Acceleration vs. Legitimacy Paradox	Cultural Readiness	Institutional values moderate speed of change.
AI as Procedural Infrastructure	Quick Wins	Clear low-risk automation areas available.
AI-Induced Evaluative Escalation	Environmental Complexity	External AI adoption increases change pressure.

AI readiness

AI Readiness Dimension	Derived From Axial Codes
Strategic Readiness	Strategic Digital Necessity
Technical Readiness	AI as Procedural Infrastructure
Organizational Readiness	Implementation–Alignment Gap
Epistemic Readiness	Epistemic Sovereignty Preservation
Operational Readiness	Contextual Precision Requirement

AI Readiness Dimension	Observation
Strategic readiness	High
Operational readiness	Moderate
Technical readiness	Moderate
Governance readiness	Low–moderate

VIII.Declaration of Authorship

I hereby declare that this thesis entitled:

“Using AI for quality assurance processes for higher education – opportunities and perceptions in transformation”

has been written independently and is the result of my own work. All sources and materials used in the preparation of this thesis have been properly acknowledged and cited in accordance with academic standards.

I further declare that this thesis has not been submitted, either in whole or in part, to any other university or institution for the award of any degree or qualification.

I am aware that any violation of the principles of academic integrity may result in disciplinary action in accordance with the regulations of Hochschule Bremen.

Place: Bremen

Date: 16 March 2026

Signature: ___________________________

Name: Mehreen Irfan Ali

Student ID: 5402386