AI INTEGRATION IN ACADEMIC QUALITY MANAGEMENT: STAKEHOLDER PERSPECTIVES FROM SOUTH AFRICAN PRIVATE HIGHER EDUCATION

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Abstract

This article presents the qualitative phase of a mixed-methods study on Artificial Intelligence (AI) integration in Academic Quality Management Systems (QMS) at South African private higher education institutions. Twelve semi-structured interviews were conducted with senior leaders, quality assurance practitioners, academic staff, and IT specialists. Thematic analysis revealed eight interconnected themes: AI in Strategic Planning, AI Literacy and Competency Development, Ethics and Data Privacy, AI in Research and Big Data Analytics, AI-Driven Teaching, Learning, and Assessment, AI in Assessment and Evaluation, Environmental Impact of AI Technologies, and Interdisciplinary Collaboration. Thirty-three subcodes identified opportunities and constraints influencing institutional readiness for AI. Insights, including AI as a change agent, contributed to a context-specific model for AI integration in higher education quality systems.

Keywords

Artificial Intelligence, Quality Management Systems, Higher Education, Thematic Analysis, Qualitative Research

JEL Classification

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1. INTRODUCTION

Artificial Intelligence (AI) has begun to reshape higher education, influencing how institutions approach administration, teaching, learning, and quality processes [1]. In South Africa's private higher education sector, efforts to integrate AI into Academic Quality Management Systems (AQMS) reveal both opportunities and complexities. Progress is uneven, often limited by regulatory uncertainty, resource constraints, and differences in institutional readiness.

Although existing literature outlines several themes for AI adoption [2][3], far less is known about how these ideas play out inside South African PHEIs, where contextual pressures differ from international settings. This article responds to that gap by presenting the qualitative phase of a sequential mixed-methods study. It draws on stakeholder accounts to understand how AI is interpreted and used within QMS processes, and how these insights can guide the development of the subsequent quantitative instrument.

2. PROBLEM STATEMENT

Although interest in the use of artificial intelligence across higher education is growing, private institutions in South Africa are grappling with the practical realities of weaving these tools into their Academic Quality Management Systems (QMS). The difficulty is not a single obstacle, but a combination of issues: uncertainty around strategic direction, uneven levels of AI understanding among staff, ethical and data governance concerns, and organisational structures that are not always aligned with digital change. Many of the existing models guiding AI adoption originate from other regions and do not fully account for the regulatory environment, resource constraints, or institutional cultures that shape the South African sector. What is still missing is evidence grounded in local experience so that an appropriate and context-ready framework for AI integration in academic quality management can be developed.

3. THEORETICAL THEMES, ANTECEDENTS AND VARIABLES

The integration of Artificial Intelligence (AI) into Academic Quality Management Systems (QMS) in South African PHEIs is informed by a conceptual framework that consolidates eight interdependent domains drawn from contemporary literature. These domains, namely strategic planning, AI literacy, ethics and data privacy, teaching and learning, research and analytics, assessment, environmental sustainability, and interdisciplinary collaboration, represent the theoretical scaffolding that guides both the study design and subsequent analysis.

First, literature emphasises that AI adoption must be strategically aligned with institutional missions, governance structures, and long-term planning priorities to ensure coherent implementation [2][4]. Second, scholars highlight the necessity of institution-wide AI literacy and competency development, integrating technical, ethical, and socio-cultural capabilities into staff and student development initiatives [4][3][5]. Third, trust in AI-enabled QMS processes hinges on robust ethical safeguards, including data protection, algorithmic fairness, and the localisation of global AI governance principles [7][8]. AI's pedagogical influence spans personalised learning, instructional support, and enhanced equity, although concerns remain regarding depersonalisation and academic autonomy [6][9][10].

Similarly, AI can strengthen research and big-data analytics when deployed with methodological rigour and appropriate human-AI oversight [11] [12]. In assessment, the promise of adaptive and formative feedback is tempered by persistent risks related to bias, reliability, and the balance between machine-generated and human judgment [8][13][14][15]. Environmental considerations are increasingly foregrounded, with studies noting the carbon and energy demands of AI systems and emphasising the need for sustainable procurement and implementation practices [9][16][17]. Finally, effective integration relies on interdisciplinary collaboration, bringing together educators, technologists, leaders, and ethicists to navigate AI's organisational, pedagogical, and ethical complexities [10] [20] [22]. Collectively, these eight themes informed the development of the semi-structured interview instrument and shaped the coding architecture applied in ATLAS. ti, ensuring conceptual continuity between the theoretical framing and empirical analysis. The complete set of themes, antecedents and variables is presented in Table 1.

Table 1: Thematic Mapping of AI Antecedents and Variables in Quality Management (Source: Author's Own Creation 2025)

THEME	ANTECEDENTS	VARIABLES
AI in Strategic Planning	1.1 Alignment with Goals	1.1.1 AI in Objectives 1.1.2 Impact on Decision-Making
AI Literacy and Competency Development	2.1 AI Literacy Across Institution	2.1.1 Need for AI Literacy 2.1.2 Ethical/Social Skills 2.1.3 Role of Development
Ethics and Data Privacy	3.1 Data Security 3.2 Bias & Fairness 3.3 Ethical Frameworks	3.1.1 Compliance 3.1.2 Trust & Transparency 3.2.1 Address Bias 3.2.2 Regulate Audits 3.3.1 Global Adaptation 3.3.2 Local Frameworks
AI in Research and Big Data Analytics	4.1 Human-AI Collaboration 4.2 Methodological Rigour	4.1.1 AI Enhances Expertise 4.1.2 Balanced Insights 4.2.1 Ethical Challenges 4.2.2 Mixed Methods
AI in Teaching and Learning	5.1 Personalised Learning 5.2 Educator Collaboration 5.3 Inequality Mitigation	5.1.1 Custom Learning 5.1.2 Standardisation Risks 5.2.1 AI for Routine Tasks 5.2.2 Focus on Creativity 5.3.1 Prevent Disparities 5.3.2 Diverse Needs
AI in Assessment and Evaluation	6.1 Enhancing Thinking 6.2 Fairness 6.3 Long-Term Impact	6.1.1 Critical Thinking 6.1.2 Holistic Evaluation 6.2.1 AI Validation 6.2.2 Bias Mitigation

		6.3.1 Student Outcomes 6.3.2 Skill Development
Environmental Impact of AI Technologies	7.1 AI Footprint 7.2 AI & Sustainability	7.1.1 Energy Use 7.1.2 Impact Reduction 7.2.1 Align with Goals 7.2.2 Green Procurement
Interdisciplinary Collaboration	8.1 Diverse Teams 8.2 Collaboration Issues 8.3 Future Models	8.1.1 Holistic Teams 8.1.2 Multi-Role Inclusion 8.2.1 Collaboration Barriers 8.2.2 Models for Strategy 8.3.1 Models for Teams 8.3.2 Field Integration

4. OBJECTIVE OF THE STUDY

This phase of the study aims to explore and contextualise stakeholder perspectives on the integration of Artificial Intelligence (AI) into Academic Quality Management Systems (QMS) within South African private higher education institutions (PHEIs), using a conceptual framework developed through prior theoretical analysis. This framework identified key themes and variables, such as strategic alignment, AI literacy, ethical governance, research integration, and pedagogical transformation, that inform institutional readiness for AI adoption.

Specifically, the qualitative phase seeks to:

- Explore how the identified themes and variables from the conceptual framework are understood, experienced, and prioritised by key institutional stakeholders;
- Examine context-specific antecedents that influence these variables, including organisational culture, resource capacity, leadership, and regulatory dynamics;
- Investigate areas of convergence and divergence in stakeholder perceptions across strategic, operational, and end-user roles;
- Refine and validate the theoretical variables through empirical insights, ensuring their relevance, clarity, and measurability for the subsequent quantitative phase;
- Generate rich qualitative evidence to guide the development of a structured survey instrument, aligned with the conceptual themes and grounded in real-world institutional contexts.

By anchoring this phase in the pre-established conceptual framework, the study ensures continuity between theory and practice, while providing an empirical foundation for measuring and evaluating AI integration in the next stage of research.

5. RESEARCH METHODOLOGY

5.1 RESEARCH APPROACH

This article offers a focused account of the qualitative phase embedded within a broader sequential mixed-methods study. The qualitative inquiry served as the foundation of the broader design, generating in-depth, context-specific insights into how institutional, human, and regulatory dimensions shape the integration of Artificial Intelligence (AI) into Academic Quality Management Systems (QMS) in South African private higher education institutions (PHEIs).

A qualitative approach was selected because AI adoption in higher education is an emergent and multifaceted phenomenon, characterised by strategic ambiguity, ethical complexity, and uneven institutional readiness [11] [23] [24]. Semi-structured interviews allowed participants to articulate their perspectives in a flexible but structured manner, ensuring that both theoretically seeded constructs and unanticipated issues could be captured [12] [25].

Data was analysed thematically to provide empirical validation and refinement of the conceptual framework developed during the earlier theoretical phase [6]. The findings of this phase form the empirical foundation for creating a contextually relevant quantitative survey instrument, thereby strengthening methodological coherence and enhancing the potential for empirical generalisation [14] [26].

5.1.1 Research Design

The qualitative phase adopted semi-structured interviews as the primary data collection method. Given the emergent and complex nature of AI adoption in PHEIs, including ethical, infrastructural, and socio-governance dimensions, a qualitative approach was most suitable for exploring stakeholder meaning-making and surfacing variables not yet fully understood in the literature [15] [26] [23]. The interview guide was structured around a pre-established theoretical framework, while remaining open to inductive insights that could refine or extend that framework in practice.

5.2 DATA COLLECTION

Semi-structured interviews were conducted to explore how stakeholders understand and experience the integration of AI within Academic Quality Management Systems (QMS). This method is particularly effective for unpacking layered organisational dynamics and divergent interpretations of emerging technologies [16] [27] [24]. Participants were selected purposively to ensure the inclusion of individuals who influence, implement, or are directly affected by AI-related decisions. The group consisted of institutional leaders, quality assurance practitioners, academic staff, IT specialists, and external industry experts. This mix provided a multi-lens view on AI readiness, policy alignment, operational capability, and pedagogical implications across South African PHEIs. Interviews were conducted virtually via Microsoft Teams, recorded with consent, and transcribed verbatim. The interview guide was shaped by the conceptual framework developed during the theoretical phase of the study [6]. It covered areas such as strategic positioning, institutional literacy and capacity, ethical and regulatory considerations, assessment practices, and organisational preparedness. While the guide ensured conceptual coverage, the flexible format allowed participants to raise issues that had not been previously considered. Notable examples included calls for formal “AI change agents,” concerns around the sector’s environmental constraints, and reflections on the uneven distribution of digital capacity, insights that broadened the original scope of enquiry [18] [23] [25] [28].

Qualitative refinement of the framework, themes, antecedents, and variables

The eight theoretical themes, developed through a literature review, were interrogated during twelve interviews to assess their relevance, completeness, and practical resonance. Rather than treating the framework as fixed, participants were asked to comment on its clarity, identify missing components, and offer context-specific refinements. This process enabled the identification of new antecedents, highlighted ambiguous boundaries between themes, and introduced nuances shaped by South African institutional realities, including constraints related to policy uncertainty, resourcing gaps, and fragmented digital ecosystems.

This iterative scrutiny aligns with broader guidance in framework development scholarship, which emphasises the importance of practitioner validation to ensure that conceptual models remain grounded, usable, and contextually responsive [19] (Patton, 2015; [24]). The outcome was a sharpened set of antecedents and variables that are theoretically coherent yet sensitive to sector complexity.

To protect anonymity in a small and easily identifiable sector, participants are described only in terms of role categories, seniority levels, and experience ranges. No institutional names or personal demographic markers are disclosed.

Table 2: Interviewee Profiles (Source: Author’s Own Creation 2025)

Interviewee Code	Role Category	Sector Position	Higher Education Experience
AIQMS005	IT Specialist	Mid-level management	5 years
AIQMS006	Governance and Registrar	Senior management	12 years
AIQMS008	Academic Head	Academic leadership	11 years
AIQMS009	Faculty	Academic staff	20 years
AIQMS010	Programme and Quality Head	Senior management	8 years
AIQMS015	Industry Expert: AI and QMS	External specialist	13 years
AIQMS016	Industry Expert: Innovation, AI, and QMS	External specialist	20 years
AIQMS017	Industry Expert: QMS and Student Experience	External specialist	17 years
AIQMS011	Executive: Quality Assurance and Governance	Executive management	14 years
AIQMS013	Chief Operations Officer	Executive management	22 years
AIQMS003	Monitoring and Evaluation Manager	Senior management	6 years
AIQMS014	Head of School (IT)	Academic and technical leadership	3 years

5.2.1 Target Population

The target population included key stakeholders involved in AI-related initiatives within South African PHEIs:

- Institutional leaders (n=2)
- IT specialists (n=2)
- Educators/faculty (n=3)
- Quality assurance personnel (n=2)
- Industry experts (n=3)

This diversity captured strategic, operational, pedagogical, and experiential perspectives essential for a comprehensive understanding of institutional AI readiness [20] [29].

5.2.2 Sampling

Participants with relevant expertise in institutional AI adoption were chosen using purposive sampling, following established best practices for exploratory qualitative research [21] [25]. Comprising 12 individuals, the final sample included institutional leaders, quality assurance practitioners, academic staff, and IT specialists from South African PHEIs. While the initial goal was 15 to 20 interviews, thematic saturation was achieved by the ninth interview, with subsequent discussions reinforcing existing categories. This aligns with the notion that saturation in focused qualitative studies typically occurs within 10 to 15 interviews [22] [23]; Squire et al., 2024). To maintain analytical independence between research phases, qualitative participants were excluded from the following quantitative survey [23] [27].

5.3 DESCRIPTION OF ANALYSIS

Thematic analysis was used to analyse the interview data as described by [24] using ATLAS.ti. This process unfolded in six iterative steps. First, the researcher immersed themself in the transcripts, reading and rereading them while noting initial impressions in memos. Next, a line-by-line coding approach in ATLAS. This led to a rich array of inductive codes, with each meaningful excerpt receiving a descriptive label. This was followed by organising these codes into a structured system, resulting in 33 subcodes embedded within eight predefined framework themes. A thorough review of the themes ensured that the coded data maintained internal coherence while being distinct from one another. Unique insights, such as the role of AI as a change agent or its application in environmental monitoring, were noted in a memo but excluded from the main codebook to maintain focus on the analysis. Subsequently, each theme and subcode was refined with clear definitions and supporting quotations added within ATLAS.ti. When it came to reporting, the final thematic map was exported to link qualitative insights to the study's objectives. The analysis utilised a hybrid approach that blended deductive and inductive methods. While coding began with a pre-established framework, emergent codes also surfaced, reflecting stakeholder perspectives that added nuance [6] [12]. The themes that emerged provided empirical validation for the conceptual framework, highlighting the predominance of ethics and governance concerns compared to weaker evidence regarding sustainability and collaboration. These findings were instrumental in shaping the quantitative survey design, transforming validated subcodes into measurable constructs [7]. This iterative process ensured methodological coherence and supported the contextual relevance of the quantitative instrument [27].

6. RESULTS

This qualitative phase examined how stakeholders in South African private higher education institutions (PHEIs) understand and implement Artificial Intelligence (AI) within their Academic Quality Management Systems (QMS). Instead of focusing on adoption, the analysis highlighted how institutional culture, governance, and ethical constraints influence the integration of AI in quality processes. Thematic analysis identified eight interconnected domains that reveal the contradictions and conditions affecting AI's inconsistent role in private higher education.

6.1 Strategic Integration and Leadership Sense-Making

Participants in the interviews highlighted a significant gap between the frequent mentions of AI in institutional discourse and its minimal role in strategic planning. One participant noted, “Strategically, there hasn't been a clearly stated stance on AI just yet. But based on recent developments, it feels like there's a growing desire to embed it into how we work in the institution to embrace AI” and further explained, “Well it's not really captured in our strategic documents, you can see that there's some movements, especially in the academic space where the teaching and learning team, they're starting to explore how AI can be used to enhance like delivery of certain programmes. They even have some pilots going” (AIQMS003). Another remarked on the disparity in their own context, explaining that although AI appears in institutional planning, “the actual integration or the efforts on execution is very scattered”, and that while leadership had expressed interest in setting annual priorities, “it isn't something that they've set out to say, hey, here is our AI project for the year” (AIQMS014). This suggests an environment where AI is acknowledged as a marker of progress but remains peripheral to core planning and decision-making. Leadership's approach further complicates the situation. Participants observed that experimentation with AI is underway, but without coordinated direction or institutional oversight. One participant explained, “The incorporation of AI into our daily activities, we are not there yet because outside of assessments, there haven't been strategic discussions about, for instance, our academics and learning and teaching. How are they using AI? Should they do it at all?” (AIQMS006). Another highlighted that AI had not yet been elevated to the level of key institutional priorities, stating, “At a strategic priorities level, I don't think AI is rising to the level of the strategic priorities. We're still very much guided by those pillars that the CHE sets” (AIQMS010). These reflections suggest a landscape where individual enthusiasm is present, but system-level support is still in the process of emerging. Participants also pointed to broader uncertainties in higher education as a contributing factor. One expert argued that senior leaders were responding reactively rather than strategically, explaining, “Institutional leaders had to respond due to necessity, but they have not necessarily defined their view on AI”, which has resulted in a context where “the operations, the integration, the policy, the governance, none of that was cemented” (AIQMS016). With limited guidance from regulatory bodies on the intersection of AI and accreditation, leaders appear hesitant, which stifles internal planning. This aligns with [32]’s assertion that institutions often use innovative language without establishing the necessary structures to implement it. Ambiguity at the system level transforms into conservative practices, despite a clear appetite for change.

6.2 AI Literacy as Institutional Capability

Participants described AI literacy as a confidence issue shaped by uneven digital foundations, limited exposure, and institutional culture. One participant noted, “There's definitely a gap in terms of skills and understanding of AI, I don't think that there's a deep understanding of what's really happening in the space” (AIQMS003). Another highlighted that basic readiness remains inconsistent, stating, “Before we even talk about AI literacy, we should be looking at digital literacy. Is it really there?” (AIQMS014). Several participants explained that restricted access makes it difficult for staff to develop competence. As one respondent put it, “ChatGPT is blocked, how are you going to try it? How are you going to test it?” (AIQMS015). Staff, therefore, feel expected to use AI responsibly, yet often lack opportunities to learn through experimentation. Generational and positional differences further affect confidence. One academic observed, “Our students are probably more advanced than we are; they are way ahead of us” (AIQMS006). By contrast, some leaders remain hesitant because “Not everyone understands how AI works, they're going to assume that if we bring in AI, we are cheating the system” (AIQMS010). Participants consistently emphasised that meaningful literacy requires targeted support rather than generic introductions. As one respondent explained, “Workshops must be short, practical, and tailored to different roles” (AIQMS003). Yet current efforts remain introductory, with another participant noting the need to shift beyond basic demonstrations toward applied capability: “That's where we're trying to develop the literacy, is like, how do you use it as a tool” (AIQMS009). Taken together, the interviews suggest that while staff are willing to learn, institutional support is fragmented, access is limited, and training lacks depth. As a result, AI competence remains uneven and dependent on individual initiative rather than coordinated development.

6.3 Ethical Governance, Data Integrity, and Regulatory Foresight

Ethics and data privacy emerged as one of the most uncertain areas for participants, who expressed practical concerns about responsibility, consent, and data handling. Interviewees described inconsistent practices, with one noting that institutions routinely upload sensitive information without adequate safeguards: “We are just taking student spreadsheet data upload with no sort of consideration as to where this data is sitting or where it’s going” (AIQMS005). This lack of clarity extended to staff experimentation with AI tools, where colleagues “take a list of students with all the personal detail on it, upload it to AI, what’s happened to the data?” (AIQMS005).

Concerns intensified around student rights and consent in the context of AI-assisted grading. One participant challenged internal assumptions that students “don’t have to know about it,” arguing instead, “How can you say you are student-centric without thinking about the student first” (AIQMS014). She emphasised that “it’s not ethical to take data from someone and not tell them how it's going to be used” (AIQMS014). Similarly, another participant raised the need for clear opt-out mechanisms: “Do we need to give students the option to opt out so that the information doesn't go via AI?” (AIQMS009). Some participants acknowledged vendor-level protections, noting that when data is processed through platforms like ChatGPT, “it doesn't end up as a spreadsheet on the open web” (AIQMS016). However, this reassurance did little to counter broader scepticism about institutional readiness. As one interviewee summarised, “My concern is that the institution does not consider ethical matters. They don't consider data privacy, being transparent with staff and students” (AIQMS014). Ethical uncertainty also extended to academic integrity, where participants highlighted risks of undetected AI-generated submissions. As one warned, “You can sort of manipulate the data, it could be totally AI, but if you submit it to a platform like Turnitin it might say 0% AI" (AIQMS005). Together, these accounts reveal a sector navigating AI adoption without sufficient policy guidance, leaving individual practitioners to negotiate ethical dilemmas with limited institutional support.

6.4 Pedagogical Compatibility and Integrity Anxiety

Across the interviews, participants expressed mixed feelings about AI's role in teaching and learning. Several noted that students increasingly default to AI, with one participant observing that learners lack "awareness around how the tools that they use work, avoiding over-reliance both for the sake of developing a creative skill set and learning" (AIQMS008). Others described how AI-generated content often lacks coherence or depth, explaining that "as soon as you bring in AI, you can have two videos that have completely different quality in one chapter, it was able to get lots of material on, the other it wasn't" (AIQMS008). Concerns were also raised about relational distance in learning environments. One educator argued that if students are given automated options, "they go to talk to a computer, it diminishes their interaction with humans" (AIQMS008). This aligns with broader fears about the erosion of dialogic learning, even as AI becomes a convenient "tutor" trained on institutional data (AIQMS005). Participants nonetheless recognised AI's potential for supporting differentiated learning. One highlighted personalised learning as "the main one" (AIQMS014). At the same time, another emphasised its ability to reduce inequity by assisting students who struggle with academic language: "You're not actually getting penalised for your inability to use language. You actually get judged on how you think" (AIQMS011). However, staff noted that pedagogical conversations remain underdeveloped, with one remarking that such discussions "have not happened at a granular level, I don't know yet to what extent, anything on paper has happened" (AIQMS006). Collectively, these accounts reflect ambivalence: AI may expand access and scaffold learning, yet risks undermining relational engagement, consistency, and depth if adopted without intentional pedagogical design [18].

6.5 Assessment Fairness and Redesign

Across the interviews, assessment emerged as one of the most unsettled areas influenced by AI, with participants highlighting concerns about authorship, integrity, and the design of tasks. One educator described how institutions are beginning to verify authenticity by generating individual writing profiles: "We get them in class to write a paragraph and then we feed that paragraph into the platform and the platform looks at the tone and the style of that writing and creates a fingerprint for each student based on their original piece of writing" (AIQMS009). This allows the system to identify originality when "a student submits an essay and it says how much of this essay is actually original student work" (AIQMS009). At system level, participants emphasised careful experimentation. One leader explained that AI is currently limited to low-risk tasks, noting, "We are exploring it for formative design and what we call ice tasks, low risk, low impact, small weighting assignments" (AIQMS016). The same institution aims to use AI to enhance marking processes, recognising that "it is the efficiency and the quality of the grading and feedback that we are trying to improve" (AIQMS016). AI is also prompting redesign of assessments themselves. One educator reported that staff are "trying to design assessments that are to a degree AI proof" (AIQMS008), while another stressed the need for higher-order cognitive demands, stating that if institutions adopt "AI proof assessments, we have to ask whether students can critique, evaluate, and explain why that is the right answer" (AIQMS010). Together, these accounts portray assessment as an area undergoing rapid change. AI offers opportunities to improve feedback and integrity processes, yet simultaneously requires a reconsideration of how tasks are structured and what counts as evidence of authentic learning [18].

6.6 AI in Research and Evidence Systems

Across the interviews, participants recognised that AI can accelerate research tasks, while also raising significant concerns about accuracy, trustworthiness, and the ethical use of data. One participant emphasised the risk of fabricated information, noting that “ChatGPT can fabricate information completely. Like make up citations. It does it very confidently” (AIQMS010). Another highlighted the need for vigilance when using AI for large-scale text analysis, explaining that “it gives you things that are not actually there” (AIQMS008). Supervisors also questioned the quality of academic work supported by AI. One explained to students that “ChatGPT is not going to do this for you. It is not going to help you pass” and emphasised that “there are shortcomings in what it can bring to the party” (AIQMS011). At a methodological level, participants worried about the risk of flawed inferences, asking, “What if the assumptions are wrong,” and cautioning that “you can use it in small pieces, but you do not want to make incorrect predictions” (AIQMS017). These concerns extended to the institutional production of evidence. One participant stated, “It is not ethical to take data from someone and not tell them how it is going to be used” (AIQMS015), while another warned that “someone still has to check the validity” of AI-assisted summaries (AIQMS003).

Overall, staff acknowledged that AI can support efficiency in literature scanning and data processing. Still, they remained cautious about its opacity, the possibility of error, and the integrity of evidence used in quality assurance. These findings align with [29] and [37], which caution that while AI can enhance productivity, it poses risks that may undermine institutional credibility if not carefully governed.

6.7 Sustainability and Institutional Accountability

Although sustainability did not dominate most interviews, several participants raised explicit concerns about the environmental footprint of AI. One participant highlighted that cloud-based systems carry substantial ecological costs, noting that “these data warehouses, what they consume is little cities that actually have to have their own power source to run these environments. We just shift the problem somewhere else” (AIQMS005). Another drew attention to hidden resource demands, explaining that “somewhere in the world there is a building with servers that are processing this. It consumes litres of water because of the cooling systems” (AIQMS010). Despite institutional commitments to green buildings and the Sustainable Development Goals, participants agreed that sustainability has not yet been integrated into AI planning. As one academic stated, “I do not think we have made that link very clearly between environmental sustainability considerations and our use of AI” (AIQMS013). Another added that “it is not just power. It is water and carbon emissions, but I do not think it is a massive consideration” (AIQMS011). Operational pressures also overshadow environmental priorities. One participant described the fragility of current systems, noting, “the system gets stuck a lot and I have lost work and had to redo it from scratch” (AIQMS008), illustrating how basic functionality becomes a more immediate concern than long-term carbon impact. Collectively, the interviews suggest that sustainability is acknowledged but deprioritised in favour of operational and strategic demands. This aligns with [30] and [19], which argue that AI’s carbon intensity remains largely invisible in higher education governance, despite [31] identifying sustainability as a cross-cutting quality dimension.

6.8 Collaboration and Socio-Technical Alignment

Participants described institutional collaboration around AI as fragmented, shaped by longstanding silo practices. One participant noted that “a lot of people are working in silos” (AIQMS005), while another explained that “aligning different departments is a challenge because we usually work in silos” (AIQMS003). This lack of integration results in uneven AI adoption, with one interviewee observing that “every director is taking their own efforts towards AI and it is not integrated or planned in a more holistic way” (AIQMS014). Several participants linked these silos to cultural barriers, including anxiety about sharing expertise. One commented that “we are too scared we lose out on something and we do not want to share knowledge” (AIQMS005). Attempts to form cross-functional teams have also been strained, with one participant recalling that “we tried to put together teams. It got quite heated. Now it is more fragmented” (AIQMS009). Time and workload pressures further limit collaboration. As one interviewee reflected, “cross-disciplinary engagement needs sufficient time. It will be more time-consuming” (AIQMS009), while another questioned whether staff were “willing to do that” (AIQMS005). Leadership emerged as central to overcoming these siloed practices. Participants emphasised the need for institutional direction, with one stating that “a stronger leadership voice would help set the tone” (AIQMS003), and another adding that “management involvement is essential for fostering cooperation” (AIQMS005). Despite these challenges, participants recognised the value of collaboration. One observed that “by doing that approach, you learn quite a lot by taking ideas from different industries” (AIQMS005), while another highlighted that cross-boundary work “helps us be more responsive and student-centred” (AIQMS009). Together, these accounts demonstrate that collaboration is fundamentally relational rather than structural, necessitating trust, openness, and effective leadership for coherent socio-technical alignment.

Synthesis

These eight domains illustrate AI integration as an interpretive and ethical struggle rather than merely a technical advancement. Leadership discourse, ethical anxiety, and structural fragmentation contribute to a setting where innovation is recognised but not fully realised. Key factors, such as strategic ambiguity, capability asymmetry, regulatory uncertainty, and cultural siloing, restrict the quality potential of AI in South African PHEIs. The next section will explore these dynamics theoretically, leading to the development of an AI-QMS Framework based on the qualitative insights gained.

7. DISCUSSION

This discussion utilises a Critical Realist framework, analysing findings through three ontological domains: the empirical (observed experiences), the actual (events regardless of observation), and the real (underlying mechanisms) [39] [41]. It connects stakeholder perceptions (empirical) to institutional practices (actual) and the structural forces shaping them (real). This approach builds on the theoretical foundations of the doctoral proposal and Article 1, where the AI-QMS Framework was conceptualised as mechanisms influencing AI integration across institutional, procedural, and experiential dimensions, maintaining coherence with the mixed-methods design.

7.1 Interpreting AI Integration Through a Quality Governance Lens

The findings reveal that integrating Artificial Intelligence (AI) within the Quality Management Systems (QMS) of South African Private Higher Education Institutions (PHEIs) hinges on alignment rather than mere adoption, influenced by governance, ethics, and institutional culture. A critical realist lens shows that visible uncertainties and uneven implementations stem from deeper issues like regulatory inertia, fragmented leadership sense-making, and a lack of institutional trust. Strategic ambiguity exposes a disconnect between rhetorical alignment and operational commitment. Institutional leaders, guided by the Council on Higher Education (CHE) and the Department of Higher Education and Training (DHET), often cite AI as a symbol of innovation but neglect its integration into planning or resource allocation [31]. This reflects morphostasis [33] [39], with routines preserving stability in the face of uncertainty. Risk aversion is rationalised due to unclear CHE or DHET guidance on AI's impact on accreditation or the Protection of Personal Information Act (PoPIA). Hence, innovation is viewed more as a symbol of legitimacy than a transformative governance approach [32]. From a quality assurance perspective, this behaviour emphasises procedural compliance. Although the CHE’s revised Quality Assurance Framework (QAF) [30] advocates for a developmental quality model, compliance metrics still dominate decision-making, limiting AI’s potential to enhance quality evidence and data analytics due to interpretive inertia rather than technical constraints.

7.2 Institutional Contradictions: Between Compliance and Innovation

The tension between compliance and innovation is a significant contradiction in the discourse of AI-QMS. Educators and quality practitioners navigate the challenge of technological efficiency alongside ethical concerns, resulting in a dynamic of resistance and experimentation. Participants highlighted the struggle to meet quality assurance standards while maintaining academic autonomy: “We have to prove fairness and validity, but CHE’s rubrics pre-date AI” (AIQMS010). This emphasises how outdated policies prompt improvisation rather than systematic innovation. Ethical data governance concerns expose vulnerabilities in the interpretation of regulations. Although [34] promotes responsible data management, participants voiced uncertainty about compliance in AI contexts: “We have no way of knowing what happens with data once it goes into these tools” (AIQMS003). [35] argue that higher education governance requires foresight to adapt to evolving ethical standards, often leading institutions to operate defensively. The lack of AI literacy in PHEIs highlights structural neglect [36]. [33] assert that AI competence encompasses ethical reasoning and pedagogical interpretation. Participants noted that literacy development is often left to individuals: “We’re told to just ‘play around’ and see what happens” (AIQMS006). [38] concept of absence as a causal condition suggests that a lack of institutional investment in capability-building constrains transformation, rather than outright resistance. The qualitative findings not only validated but also refined the original eight-domain conceptual framework, as demonstrated in Table 1, which maps original themes to the emergent capability domains identified in this study. Table 3 summarises the linkage between the original framework themes and the refined capability domains, highlighting how qualitative insights strengthened conceptual clarity.

Table 3: Alignment of Original Themes with the Refined Capability Domains (Source: Author's Own Creation 2025)

Original Theme	Mapped To New Capability Domain	Reason (Based on Findings 6.1–6.8)
AI in Strategic Planning	Interpretive Governance	Leadership ambiguity, strategic misalignment, symbolic adoption, and siloed planning
AI Literacy and Competency Development	Operational Capability	Literacy gaps, ethical confidence, training absence, and practical skill development
Ethics and Data Privacy	Ethical - Regulatory Infrastructure	Data ethics, PoPIA uncertainty, trust, transparency, compliance concerns
AI in Research and Big Data Analytics	Ethical - Regulatory Infrastructure and Operational Capability	Research validity (ethics), research workflows (capability)
AI in Teaching and Learning	Operational Capability	Pedagogical compatibility, educator use, and integrity anxiety
AI in Assessment and Evaluation	Operational Capability	Fairness, bias mitigation, assessment redesign, and integrity
Environmental Impact of AI Technologies	Ethical–Regulatory Infrastructure	Sustainability accountability, institutional avoidance, and CHE QAF requirements
Interdisciplinary Collaboration	Interpretive Governance and Operational Capability	Cultural silos (governance); teamwork, implementation (capability)

7.3 Towards an AI–QMS Framework

This study conceptualises AI integration as an emergent capability ecology, consisting of three interacting dimensions: interpretive governance, ethical–regulatory infrastructure, and operational capability. These elements determine the quality of AI–QMS integration through leadership's sense-making, ethical foresight, and pedagogical alignment. Interpretive governance focuses on how leadership translates AI's potential into organisational goals. Hernández-Lara and Serradell-López (2024) assert that digital transformation in higher education requires a shared understanding at both strategic and operational levels. A lack of interpretive coherence can lead to fragmentation, where faculties, QA units, and IT departments pursue parallel initiatives without a unified vision. The ethical–regulatory infrastructure involves norms and oversight mechanisms that build trust. [36] argue that the legitimacy of AI governance arises from transparency rather than control. Participants note that while ethics are emphasised, operational trust remains weak, policies are reactive, and data protection is inadequate, revealing institutional vulnerabilities. Operational capability includes practices for integrating AI into quality processes. Educators experience "integrity anxiety" [9], which highlights conflicts between technology and moral expectations. Assessment challenges necessitate adaptive design and fairness [13]. Collaboration is critical, as siloed cultures among QA, IT, and academic staff impede integration [21].

7.4 Theoretical and Policy Implications

These findings shift the discourse on technological change in higher education from adoption to alignment. Unlike the [40] linear Diffusion of Innovation framework, this study illustrates that AI integration is iterative and shaped by institutional meaning systems. Contemporary socio-technical theorists [41] [42] emphasise that successful digital transformation requires the alignment of technological and social subsystems, a delicate balance in AI-enabled quality management. The emergent AI-QMS Framework enhances the field by incorporating ethical governance and regulatory foresight within a systems framework of organisational capability. This reconceptualisation has several policy implications. The CHE and DHET must clarify AI's alignment with quality standards, data integrity, and academic integrity. Institutional leaders are tasked with translating these directives into governance narratives that encourage accountability and innovation. Professional development should focus on fostering ethical confidence that combines technical competence, policy awareness, and moral judgment. Finally, sustainability accountability needs to transform from rhetoric to measurable performance, aligning with the CHE's (2024) transversal indicators for sustainable quality systems.

7.5 Pathway to Quantitative Validation

The refined conceptual categories from this qualitative phase will inform the development of the quantitative instrument, which will measure how variations in interpretive governance, ethical–regulatory infrastructure, and operational capability predict perceived alignment between AI use and institutional quality outcomes. This shift from interpretive description to causal exploration illustrates the critical realist principle of explanatory depth, identifying not only what phenomena occur but also why they occur within specific structural and cultural contexts.

7.6 Refinement of the Conceptual Framework

The qualitative analysis reaffirmed the original conceptual framework but refined it into a capability-based model that highlights how governance, ethics, and institutional practice interact to shape AI–QMS integration. The eight initial thematic domains are recast as relational capabilities rather than stand-alone themes. Case in point, strategic planning is now interpreted through leadership sense-making and institutional risk perception, while AI literacy is transformed into ethical confidence, reflecting the merging of technical ability with responsible judgment. Ethical governance incorporates regulatory foresight aligned with evolving CHE and DHET directives, and teaching and assessment are reframed around pedagogical compatibility and academic integrity. Research is linked to the integrity of evidence in an algorithmic environment, sustainability to ecological accountability, and collaboration to socio-technical alignment, where human and technological systems are integrated through shared purpose. These refinements shift the framework from a descriptive thematic taxonomy to an interactive capability ecology comprising three interdependent layers: interpretive governance, ethical-regulatory infrastructure, and operational capability. Because these layers are reciprocal, the framework positions AI-QMS integration as a dynamic institutional system responsive to risk, ethics, and collaborative culture. For the quantitative phase, this revised framework provides measurable constructs for examining how these capabilities relate to perceived institutional alignment. Table 4 summarises how each of the original eight domains aligns with the refined capability structure, illustrating the shift from thematic categories to interlinked institutional capabilities.

Table 4: Alignment of Original Themes with the Refined Capability Domains (Source: Author's Own Creation 2025)

New Capability Domain	Original Theme	Revised Antecedents	Revised Variables
1. Interpretive Governance	AI in Strategic Planning	1.1 Alignment with institutional goals 1.2 Leadership sense-making 1.3 Risk perception 1.4 Strategic coherence 1.5 Resource commitment	1.1.1 AI included in institutional objectives 1.1.2 Influence of AI on decision-making 1.2.1 Degree of strategic ambiguity 1.2.2 Extent of leadership clarity 1.5.1 Level of AI resource allocation
	Interdisciplinary Collaboration	1.6 Diversity of teams 1.7 Collaboration structures 1.8 Cultural/organisational silos	1.6.1 Cross-department integration 1.7.1 Collaboration barriers 1.7.2 Strategic collaboration models 1.6.2 Holistic or multi-role team inclusion
2. Ethical - Regulatory Infrastructure	Ethics and Data Privacy	2.1 Data security readiness 2.2 Fairness and bias awareness 2.3 Ethical governance frameworks 2.4 Regulatory foresight	2.1.1 Compliance with PoPIA 2.1.2 Trust and transparency in AI processes 2.2.1 Bias mitigation practices 2.3.1 Audit protocols 2.4.1 Adaptation of global and local ethical standards
	AI in Research and Analytics	2.5 Ethical research conduct 2.6 Data integrity expectations	2.5.1 Validation of AI outputs 2.5.2 Trustworthiness of AI-generated evidence 2.6.1 Ethical alignment of mixed-methods research
	Environmental Impact of AI Technologies	2.7 Awareness of AI footprint 2.8 Sustainability alignment with institutional goals	2.7.1 Energy consumption accountability 2.7.2 Environmental impact reduction strategies 2.8.1 Sustainability-aligned procurement
3. Operational Capability	AI Literacy and Competency Development	3.1 Institutional AI literacy levels 3.2 Ethical and social reasoning skills 3.3 Availability of staff development opportunities	3.1.1 Need for institutional AI literacy 3.1.2 Ethical confidence 3.3.1 Staff capability to use AI in QMS tasks 3.3.2 Effectiveness of professional development provisions

	AI in Teaching and Learning	3.4 Pedagogical adaptability 3.5 Educator collaboration 3.6 Equity considerations	3.4.1 Personalised learning applications 3.4.2 Standardisation risks 3.5.1 AI for routine academic tasks 3.5.2 Creativity and higher-order thinking support 3.6.1 Disparity prevention 3.6.2 Support for diverse learning needs
	AI in Assessment	3.7 Fairness expectations 3.8 Long-term educational impact 3.9 Assessment redesign needs	3.7.1 Critical thinking enhancement 3.7.2 Holistic evaluation 3.7.3 Validation of assessments 3.8.1 Bias mitigation 3.8.2 Long-term student outcomes 3.9.1 Skill development through AI-enabled assessment
	AI in Research and Analytics	3.10 Human - AI methodological balance 3.11 Research workflow practices	3.10.1 AI enhances expertise 3.10.2 Balanced human - AI insight generation 3.11.1 Verification protocols for AI-generated references

8. LIMITATIONS

This qualitative inquiry offers valuable insights into stakeholder perceptions of AI integration in Academic Quality Management Systems (QMS), though several limitations exist. Purposive sampling restricts the generalizability of findings to other institutions [25]. Additionally, self-reported data may be subject to social desirability or recall bias, potentially leading participants to exaggerate their institution's readiness and downplay challenges [43] [44]. Despite efforts to include diverse voices, part-time staff and regulatory bodies were underrepresented. While thematic saturation was achieved across eight framework themes, areas such as environmental sustainability and interdisciplinary collaboration require further exploration. These limitations underscore the need for a subsequent quantitative inquiry to validate the findings and assess the robustness of the identified variables.

9. FUTURE RESEARCH

Future research should conduct a quantitative study to assess the significance and relationships of variables across a broader range of South African private higher education institutions (PHEIs), testing the framework's robustness and enabling comparisons among different stakeholders. Additionally, qualitative exploration could focus on three areas: comparing private and public institutions to understand how governance, resources, and regulatory oversight impact AI integration; conducting longitudinal studies to track changes in perceptions and practices with AI adoption; and investigating interdisciplinary collaboration's influence on the ethical and pedagogical aspects of AI implementation [20]

10. SUMMARY

This article discusses the qualitative phase of a mixed-methods study focused on integrating Artificial Intelligence (AI) into Academic Quality Management Systems (QMS) at South African private higher education institutions (PHEIs). Utilising a theoretical framework, the study conducted thematic analysis of semi-structured interviews, identifying eight interrelated themes: AI in strategic planning, AI literacy and competency, ethical considerations and data privacy, AI in research, teaching and learning, assessment, environmental sustainability, and interdisciplinary collaboration. The findings reveal insights into stakeholder experiences, highlighting common issues like strategic ambiguity and uneven AI literacy, alongside emerging concerns regarding environmental sustainability and interdisciplinary collaboration. These outcomes validate and expand the initial framework, emphasising factors like resource allocation, gaps in staff-student proficiency, and policy consistency. This phase enhances the understanding of institutional readiness for AI adoption in South African PHEIs. The insights will guide the creation of a structured quantitative survey for the next phase, ensuring measurement items are theoretically sound and relevant to the context. Overall, the study aims to inform AI policy and practice within quality assurance frameworks, promoting responsible and context-sensitive AI integration in higher education.

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