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Measuring Artificial Intelligence Integration in South African Private Higher Education: Applying a Refined Academic Quality Management Model

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ABSTRACT

This study applies a refined model of Artificial Intelligence (AI) integration into Academic Quality Management Systems (AQMS) within South African private higher education. It builds on prior validation through exploratory factor analysis and reliability testing to examine how institutional factors relate to stakeholders' perceptions of AI integration. Survey data from higher education and education technology stakeholders were analysed using PLS-SEM, correlation, multiple regression, and descriptive statistics. The results show moderate explanatory power, with regression indicating stronger overall model performance than PLS-SEM. Across analyses, Research Governance and Responsible AI Use emerged as the most consistent and statistically supported factor associated with AI_QMS. Strategic Planning and AI in Teaching and Learning also contributed positively, although their effects varied by method. In contrast, AI Literacy and Competency Development and Assessment and Evaluation produced inconsistent results, including negative regression coefficients, which are interpreted cautiously due to shared variance and measurement limitations. Other factors, including Ethical Considerations and Data Privacy, Environmental Impact, and Interdisciplinary Collaboration, did not demonstrate independent explanatory power in multivariable models. The findings highlight that observable institutional activity does not necessarily translate into consistent integration within academic quality systems. The study contributes a multi-dimensional framework that distinguishes between strongly supported relationships, method-dependent effects, and areas requiring further measurement development. Practically, the model provides institutions with a structured approach to assess and strengthen AI integration within academic quality management.

Keywords: Artificial Intelligence, Academic Quality Management Systems, Private Higher Education, South Africa, Governance, Quality Assurance
JEL Classifications: I23, O33, M10

1. INTRODUCTION

Generative artificial intelligence (generative AI) is reshaping the way higher education institutions manage teaching, assessment, research, student support, and academic quality assurance. Its use is no longer confined to institutionally approved systems such as learning management platforms or licensed software. Instead, students, academics, and professional staff increasingly access AI tools independently, often beyond formal institutional structures. While this expanded access creates opportunities for innovation and efficiency, it also presents challenges for institutional oversight, policy alignment, and quality assurance. Contemporary policy discourse reflects this shift. UNESCO (2023) frames generative AI not merely as a technological resource but as an institutional responsibility, emphasising the need for coherent policy frameworks, human capability development, and sustained oversight to preserve educational integrity. Similarly, recent studies indicate that institutional responses are moving from general concern toward more targeted guidance on teaching, assessment, and ethical AI use.

Within the South African private higher education context, these challenges are particularly pronounced. AI integration extends beyond technological adoption to intersect with core institutional

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functions, including quality assurance systems, academic standards, assessment credibility, data protection, and institutional accountability. Legislative requirements, such as the Protection of Personal Information Act (POPIA), impose specific obligations on organisations handling personal data; these obligations become more complex in AI-driven environments, where automated systems process sensitive information. In this setting, academic quality management cannot be treated as peripheral to AI adoption. Academic quality management depends on the integrity of data, defensible decision-making processes, and transparent governance structures embedded within the continuous quality cycle of planning, implementation, review, and improvement.

This study builds on an earlier phase of research in which a conceptual model of AI integration into Academic Quality Management Systems (AQMS) was developed and empirically refined through data suitability testing, reliability assessment, and exploratory factor analysis. The resulting model comprises eight interconnected domains: Strategic Planning, AI Literacy and Competency Development, Ethical Considerations and Data Privacy, AI in Teaching and Learning, Assessment and Evaluation, Research Governance and Responsible AI Use, Environmental Impact of AI Technologies, and Interdisciplinary Collaboration. Prior work established the internal coherence of these constructs but did not investigate their behaviour within an applied institutional context.

This study examines how these factors relate to stakeholders' overall perceptions of AI integration within academic quality management. It moves beyond measurement validation to investigate the extent to which the retained factors explain variation in AI_QMS and what their relationships reveal about current institutional practice. In doing so, the article contributes to a more nuanced understanding of AI integration, not as a single condition or readiness state, but as a multifaceted process shaped by governance, capability, pedagogy, and institutional coordination.

1.1. Problem Statement

An earlier phase of the full doctoral study developed a measurement framework for the integration of AI into Academic Quality Management Systems in South African private higher education. Exploratory factor analysis and internal reliability testing provided empirical support for the retained structure, clarifying which items were essential to remove or refine, which then allowed the model to be applied to examine how its factors relate to AI_QMS, and what those relationships divulge about current institutional practice. This is particularly relevant in private higher education, where AI affects academic planning, assessment integrity, research practices, data protection, and quality assurance. As it is improbable that advancement in any of these areas would occur at the same pace, the model accommodates the variances for study within a single academic quality management framework.

The problem addressed in this study is whether the retained AI QMS factors explain variation in overall AI integration and how the results contribute to understanding current institutional practice. PLS-SEM and multiple regression are used to examine the factors together, Pearson correlations show their individual relationships with AI_QMS and with one another, and descriptive statistics provide a view of how respondents rated each area.

1.2. Objectives

The purpose of the study is to examine how the AI QMS integration model performs in the South African private higher education context. It considers whether the retained factors explicate variation in the perceived extent of AI integration into academic quality management systems and what the data discloses about current institutional practice.

The study is guided by two objectives, namely to:

- Examine the relationships between the retained AI QMS model factors and the extent of AI integration into academic quality management systems
- Apply the model to measure current AI QMS practice and identify areas requiring further institutional deliberation.

2. LITERATURE REVIEW

2.1. Measuring AI Integration as an Academic Quality Management Issue

Measuring AI integration in higher education is not the same as measuring whether an institution has adopted AI tools. Although such tools may indicate AI activity, they do not necessarily indicate whether AI use is governed, ethically managed or connected to institutional academic quality processes. The use of generative AI can occur informally and outside established institutional systems, platforms and protocols, thereby making this distinction important. The OECD links this challenge to the broader digital education ecosystem, in which governance, policy alignment, human capacity and risk management must form part of education systems' responses to generative AI (OECD, 2023).

Academic quality management adds a complex layer to this ecosystem, since quality systems are concerned not only with teaching and learning delivery, but also with assessment integrity, evidence of decision-making, research credibility, policy compliance, student support, institutional performance, strategic review and continuous improvement. Once AI affects these functions, it becomes part of the quality system itself. In South Africa, the Council on Higher Education has not treated AI as digital innovation alone, but has positioned it as deeply interlinked with ethics, governance, institutional responsibility and academic standards (CHE, 2024). Measuring AI integration therefore requires more than a readiness or adoption score. It must consider whether AI has been strategically located, whether staff have the capability to use it, whether data and privacy risks are appropriately governed, whether assessment remains credible and integrity-driven, and whether research continues to be subject to human oversight. UNESCO's guidance on generative AI similarly underscores policy, capacity development and human-centred oversight, and does not assume that educational benefits follow automatically from access to, or use of, AI tools (UNESCO, 2023).

Consequently, the AI QMS model used in this article treats AI integration as a set of related academic quality conditions and

approaches integration through the institutional arrangements surrounding AI use, rather than through a singular lens of technology adoption. Since strategic direction, human capability, ethical safeguards, teaching and assessment practice, research governance, sustainability and collaboration may develop at different rates, these areas were measured separately to understand how the broader pattern of AI QMS integration takes shape, without if progress in one part of the institution reflects integration across the entire institutional ecosystem.

2.2. Using Validated Models to Measure AI Integration

AI integration has been approached from several theoretical positions, with some studies measuring whether individuals intend to use AI, others examining organisational readiness to implement AI tools, and only a limited number considering the impact of AI on institutional practices once implementation has occurred.

At the level of individual use, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) remain influential because both models link technology use to users' perceptions of value, effort and enabling conditions. TAM3 retains perceived usefulness and perceived ease of use but positions these constructs within broader influences such as subjective norms, job relevance, perceptions of external control, computer self-efficacy and user experience (Venkatesh and Bala, 2008). UTAUT similarly arranges influences around performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). The distinction between the models is less important here than their shared endpoint, since both focus ultimately on behavioural intention and technology usage. Recent AI-related studies have extended this logic by considering technology value, familiarity, training, access, organisational support, personal innovativeness and technology readiness (Sova et al., 2024; Fang et al., 2025). These studies help explain why access to AI technology does not necessarily produce engagement or quality benefits; they also show that willingness to use AI tools differs from whether such use is academically sound or institutionally governed.

Diffusion of Innovation (DOI) theory approaches commitment to technology use less as an isolated decision and more as a process that unfolds through a social system. Relative advantage, compatibility, complexity, trialability and observability explain why an innovation may gain traction in one setting while remaining marginal in another (Rogers, 2003), offering a plausible explanation for the irregular way in which AI systems and tools enter higher education spaces. Teaching staff may experiment with generative AI before assessment policies are revised; researchers may use it while disclosure rules remain unsettled; and administrative units may automate routine work without a common institutional position on data use. DOI can therefore explain variation in the pace, visibility and acceptance of AI, but diffusion does not indicate that the resulting practices form a coherent institutional ecosystem.

The Technology-Organisation-Environment (TOE) framework introduces conditions beyond the individual adopter by considering technological feasibility, organisational resources and external influences such as regulation, market forces and sectoral pressure as part of the same implementation environment (Tornatzky and Fleischer, 1990). The perspective therefore changes from users and their receptiveness to technology, to whether the institution has the capacity and latitude to commence with responsible technological implementation. Since the boundaries between these explanations are not always clear in empirical work, recent studies have begun combining them. Abulail et al. (2025), for instance, integrated TAM, DOI and TOE into a higher education model that included user perceptions, technology features and organisational conditions. The resultant framework offers a fuller explanation of adoption intention, yet adoption intention remains its endpoint, and strategic alignment, research oversight or assessment credibility appear only when they influence technological acceptance, not as academic quality outcomes requiring evaluation.

AI-readiness models advance the institutional emphasis by recognising that technical preparedness and human preparedness may not develop at the same pace or along the same tracks. The dual-level AI readiness model developed by Hržica et al. (2025) combines TOE and UTAUT at the enterprise and individual levels, thereby facilitating joint consideration of infrastructure, institutional support, environmental pressure and user expectations within the same readiness structure. This is particularly advantageous for institutions where staff eagerness to adopt technology may run ahead of policy, or where infrastructure has been acquired without the prerequisite responsible-use capability. It is noted, though, that readiness remains a condition that precedes or supports implementation, and is not a determinant of the type or quality of academic practices that follow.

The socio-technical perspective moves the discussion closer to institutional integration. Grounded in Socio-Technical Systems Theory, it emphasises the interdependence of people, technologies, work processes and organisational structures (Trist and Bamforth, 1951). In socio-technical approaches, AI is handled neither purely as an enterprise investment nor as a technology component awaiting acceptance, but as a technology that may adjust professional judgement, work design, institutional norms and relations of responsibility. Hou (2025) similarly differentiates AI into pedagogical infrastructure, curricular or professional content and a socio-technical context that affects institutional culture and educational values. This typology makes an important separation between the presence of AI and its deeper institutional incorporation, since a higher education institution may report extensive AI use without having reconsidered curriculum design, accountability, academic decision-making or academic quality assurance.

UNESCO's AI Competency Framework for Teachers and Chan's (2023) AI Ecological Education Policy Framework address aspects of this institutional problem from more specialised perspectives. UNESCO's framework identifies 15 competencies across a human-centred mindset, AI ethics, foundations and applications, pedagogy and professional learning (UNESCO, 2024), thereby clarifying the capabilities expected of educators. However, it does not measure whether these capabilities are consistently supported across institutions or connected through

formal quality management processes. Chan's (2023) framework brings pedagogical, governance and operational responsibilities into closer contact, placing teaching practice alongside privacy, security, accountability, infrastructure and training. The framework is therefore more aligned with integration across institutional functions than models directed towards behavioural intention, because it acknowledges that pedagogical use depends on governance and operational arrangements. It is critical to note, however, that its purpose remains embedded in policy development rather than the measurement of AI within an academic quality management system.

The established models address diverse aspects of the same institutional challenge rather than competing explanations. TAM, TAM3 and UTAUT provide clarity on why people engage with AI, while DOI explains how that engagement spreads. TOE and the dual-level AI readiness model identify the enterprise and external conditions that support implementation, while Socio-Technical Systems Theory, Hou's (2025) typology, UNESCO's AI Competency Framework for Teachers and Chan's (2023) AI Ecological Education Policy Framework examine the institutional responsibilities that AI use creates. There is therefore no single perspective or model that covers all these aspects and even combining them does not inevitably resolve the variance between adoption and academic quality. Whether AI use has become part of the structures through which academic work is planned, governed, reviewed and improved remains essentially under-measured.

2.2.1. Advantages and disadvantages of validated models

The value of validated models lies in the accumulated evidence supporting their constructs, as their variables have been tested in different settings, research instruments are often available, and comparisons across studies are possible. They also provide analytical discipline: a TAM- or UTAUT-underpinned study specifies whose acceptance is being examined, DOI shifts attention to the characteristics and social movement of the innovation, and TOE forces the analysis beyond user preferences to institutional capacity and external pressure. Combining models can lessen some of the constraints associated with a single perspective. Abulail et al. (2025) showed how personal beliefs, innovation characteristics and institutional conditions can be examined together, while the dual-level AI readiness model of Hržica et al. (2025) makes it possible to separate user and institutional preparedness, which is particularly useful where AI implementation is uneven and low adoption cannot simply be attributed to staff resistance or limited technical access.

The limitations of these models become more visible when the outcome alters from adoption to academic quality. Perceived usefulness may explain why a lecturer uses generative AI, but it cannot determine whether the resulting assessment still provides credible evidence of learning. Similarly, enterprise readiness may indicate that infrastructure, skills and leadership support exist, yet say little about authorship, research verification or how personal data should be used. Diffusion may show that AI use has become prevalent, while leaving unanswered who is ultimately accountable when the technology produces unreliable or unfair outcomes. Socio-Technical Systems Theory, Hou's (2025) typology, UNESCO's AI Competency Framework for Teachers and Chan's (2023) AI Ecological Education Policy Framework bring these questions closer to the core of the analysis and are valuable for interpretation and institutional guidance. However, they do not necessarily provide a validated measure of integration; capabilities, risks and responsibilities are identified, but the extent to which AI is incorporated into academic quality management is not established.

The differentiation is therefore one of purpose: established models explain acceptance, diffusion, readiness, organisational conditions or responsible practice, whereas the present study is concerned with the relationship between those conditions and the institution's capacity to maintain academic quality. The outcome is not purely whether AI is used, but whether that use is associated with strategy, staff capability, teaching, assessment, research governance, privacy, sustainability and coordination across institutional functions. This difference provides the basis for considering a bespoke AI QMS model.

2.3. Bespoke Models to Measure AI Integration

A bespoke model becomes necessary when the research problem is defined by a particular institutional purpose. In the present study, the concern is not limited to whether AI is accepted or whether its use has spread; rather, the institution remains accountable for what transpires once AI enters teaching, assessment, research, student administration and academic decision-making. Each of these areas affects the academic quality produced, and that impact cannot be inferred purely from whether the technology has been adopted.

The South African Quality Assurance Framework (QAF) provides a stronger basis for this shift in emphasis. The Council on Higher Education (CHE) links quality to institutional mission, academic planning, governance, accountability and continuous improvement (CHE, 2012). Within this framework, the ideas of fitness for purpose and fitness of purpose are especially relevant to AI integration because they move the inquiry from use to institutional responsibility (CHE, 2022).

Fitness for purpose concerns whether an institution has the arrangements and capacity needed to fulfil its own mission and academic plans. When positioned in relation to AI, this involves more than access to the tools themselves; it also requires strategic underpinning, staff capability development, credible teaching and assessment practices, responsible research oversight, and coordination across academic, quality management, information technology and compliance functions. AI may therefore be widely adopted across an institution while the institution still lacks the internal systems needed to use it consistently, responsibly and in a manner that is fit for its intended educational purpose.

Fitness of purpose extends the evaluation beyond internal capability and challenges whether the direction itself is suitable in relation to the wider responsibilities of higher education. AI use may be efficient and popular, yet still raise concerns about academic standards, privacy, authorship, fairness and environmental cost. These matters are not secondary to implementation, but form part of the judgement on whether AI serves a legitimate educational purpose that can be defended by the institution.

This is where the AI QMS model departs from established acceptance, diffusion, readiness and implementation frameworks. TAM3 and UTAUT elucidate why users engage with technology and which conditions shape intention and use, while DOI considers how adoption moves through a social system. TOE brings enterprise capacity, infrastructure and external pressure into the analysis, whereas Socio-Technical Systems Theory, Hou's (2025) typology, UNESCO's AI Competency Framework for Teachers and Chan's (2023) AI Ecological Education Policy Framework extend the discussion to professional practice, capability, governance and institutional responsibility. These standpoints are useful, although they were developed around different outcomes and do not provide a direct measure of AI integration within academic quality management.

The AI QMS model was designed around this gap. It aims to examine arrangements for the use of AI and whether these are sufficiently developed to sustain academic quality, rather than treating AI usage, readiness or the presence of policy as sufficient evidence of integration. Recent work by Isaifan and Hasna (2025), through their policy-to-practice quality assurance model, moves in a similar direction by linking AI implementation to readiness, governance, data quality, review processes and human expertise. Chan's (2023) AI Ecological Education Policy Framework also brings pedagogical, governance and operational responsibilities into a single institutional structure, while Hou (2025) differentiates visible AI use from deeper socio-technical integration that affects institutional culture and practice. These approaches strengthen the case for gauging AI beyond behavioural intention, but they remain focused mainly on policy, capability and implementation, and do not provide a tested measure of AI integration across the combined functions of an academic quality management system.

The eight factors in the AI QMS model were developed to address this institutional gap by bringing strategy, capability, teaching, assessment, ethics, research governance, sustainability and interdisciplinary collaboration into one structure that can be inspected empirically. The purpose is to assess whether the conditions associated with AI use have been incorporated into the systems through which academic quality is planned, governed, reviewed and improved.

2.3.1. Advantages and disadvantages of bespoke models

The principal advantage of a bespoke model is that it can be built around the decisions institutions must make to align with their compliance and regulatory requirements. The constructs were selected because they reflect the management problem under investigation and make it possible to examine assessment credibility, responsible research, data protection, sustainability and interdisciplinary collaboration across institutional functions, alongside strategy, capability and teaching practice.

This contextual alignment is particularly important in South African private higher education, where institutions differ in size, mission, resources, programme profile and technological capacity, while each remains accountable for the quality of its academic provision. The CHE's principles of fitness for purpose and fitness of purpose also demand evidence, beyond technology adoption, that institutions have the necessary arrangements to support their academic missions and that the purpose being served remains appropriate to the broader responsibilities of higher education. Accordingly, a model grounded in academic quality management is better matched to these questions than one centred mainly on intention, readiness or adoption.

A bespoke model can develop through several forms of evidence, and in this study, the AI QMS model originated through conceptual exploration, was subsequently refined through stakeholder accounts, and was later tested through data suitability assessment, reliability analysis and exploratory factor analysis. The initial structure was not retained unchanged, as some items were removed, constructs were narrowed and the empirical results shaped the form in which the model was applied.

This flexibility also creates difficulty, since a purpose-built model does not benefit from the testing history of TAM3, UTAUT, DOI or TOE. The constructs require careful definition, and their performance may vary across samples or institutional settings. Related areas may also overlap statistically, given that strategy, governance, capability and academic practices do not operate in silos. The present analysis illustrates this problem: AI Literacy and Competency Development, and Assessment and Evaluation remained important to the academic quality question, but their measurement performance was weak in the PLS-SEM analysis. Including these constructs remains conceptually defensible, although their current item structure requires modification, confirming that contextual relevance cannot replace empirical testing.

Since the earlier models explain important aspects of acceptance, diffusion, readiness and implementation, while the AI QMS model examines whether those conditions have been translated into arrangements that support academic quality, the established and bespoke models should not be viewed as mutually exclusive.

2.4. From Model Validation to Model Application

The full doctoral study followed a staged process in which conceptual and qualitative work first identified the institutional areas considered relevant to AI integration into academic quality management. These areas were then operationalised as measurable constructs and empirically surveyed. Exploratory factor analysis showed that the dominant structure could be retained, although several constructs required item removal or narrower interpretation before further application.

The retained factor structure, which serves as the starting point for the present analysis, needs to be reported beyond whether each factor is internally coherent. It also requires examination of how the factors relate to the overall perceived extent of AI integration into QMS within institutions. It is important to note that a construct may perform adequately in exploratory factor analysis but may not make a clear independent contribution when located alongside the other factors in a broader statistical model.

PLS-SEM was therefore used to examine the eight retained factors together and to determine which paths to AI_QMS were

statistically supported, while Pearson correlations showed how each factor related to AI_QMS before the remaining factors were considered. Multiple regression was then used to estimate their contributions when considered simultaneously. Construct-level descriptive statistics provided an additional view of how respondents rated current practice across the model areas. The combined analysis therefore links the measurement structure to its intended application in South African private higher education.

2.5. Hypotheses

The relationship analysis examined whether the eight retained factors were associated with respondents' overall perception of AI integration into academic quality management systems. Each factor represents a different institutional area within the model, and its relationship with AI_QMS was therefore tested empirically.

The general hypothesis was stated as follows:

- H_1: The retained AI QMS model factors are significantly related to the overall perceived extent of AI integration into Academic Quality Management Systems

To test the relationships at the factor level, H1 was divided into the hypotheses presented in Table 1. The formal hypothesis decisions are based on the multiple regression results, which show the contribution and statistical significance of each factor when all eight predictors are considered together. The PLS-SEM findings provide an additional assessment of the structural relationships.

3. RESEARCH METHODOLOGY

3.1. Research Design

The study used a quantitative, cross-sectional design within a larger sequential exploratory doctoral study. Earlier phases of the study conceptualised and qualitatively developed the AI QMS model, drawing on existing literature and stakeholder insights. Subsequently, the themes derived from the respective stakeholder engagements underwent a validation phase that tested the proposed survey items as an empirical measurement structure. That process exhibited that the original model was broadly defensible, with some refinement needed. Three constructs were retained unchanged, while five required item-level refinement. The outcome was a revised AI QMS integration model with a clearer empirical structure for application.

Table 1: Factor-level hypotheses for the refined AI QMS integration model

Hypothesis	Expected relationship
$H_{1.1}$	Strategic Planning is significantly related to overall AI QMS integration.
$H_{1.2}$	AI Literacy and Competency Development is significantly related to overall AI QMS integration.
$H_{1.3}$	Ethical Considerations and Data Privacy is significantly related to overall AI QMS integration.
$H_{1.4}$	AI in Teaching and Learning is significantly related to overall AI QMS integration.
$H_{1.5}$	Assessment and Evaluation is significantly related to overall AI QMS integration.
$H_{1.6}$	Research Governance and Responsible AI Use is significantly related to overall AI QMS integration.
$H_{1.7}$	Environmental Impact of AI Technologies is significantly related to overall AI QMS integration.
$H_{1.8}$	Interdisciplinary Collaboration is significantly related to overall AI QMS integration.

This phase of the study applies the retained factors to the AI_QMS outcome, concentrating on how they relate to respondents' valuation of AI integration into academic quality management systems. The cross-sectional design was well-suited because it captured stakeholder perceptions at a specific point in time and enabled the model to be applied to the current institutional context. Gogo and Musonda (2022) describe exploratory sequential mixed-method design as valuable when a preliminary exploratory phase informs later quantitative work, especially in context-specific studies.

3.2. Population and Sampling

Stakeholders familiar with or professionally involved in Artificial Intelligence, academic quality management, higher education leadership and governance, teaching and learning, assessment, research, information technology, quality assurance, or education technology comprised the target population for this study. Although the study remained focused on South African private higher education, the stakeholder group was intentionally broad because AI integration into academic quality management does not sit within a single institutional function but cuts across academic work, quality assurance, leadership, IT, research, operations and external education technology practice. Academic staff, quality assurance practitioners, institutional leaders, IT professionals, researchers, operational staff and EdTech specialists were therefore considered pertinent to the study, reflecting the model's scope across governance, capability, pedagogy, assessment, research, data responsibility, sustainability and collaboration.

A non-probability purposive sampling strategy was followed, given that the study required participants with some level of informed exposure to AI, higher education, academic quality, or educational technology, rather than respondents drawn from the public. Purposive sampling was suitable because it allowed participants to be selected based on their knowledge, role, or experience in relation to the research question (Tajik et al., 2025).

The survey invitation was shared through professional networks and public digital platforms, including LinkedIn, higher education networks, private higher education contacts and EdTech-related forums. Because these channels were open and network-based, it was not possible to determine how many eligible individuals saw the invitation, and a formal response rate was therefore not calculated. In total, 85 survey cases were recorded, of which 82 were eligible for inclusion after consent screening. The usable sample size differed across the statistical procedures due to missing data: the validation phase used 72 cases for the descriptive analysis, KMO and Bartlett tests, exploratory factor analysis and reliability analysis, while the correlation and regression analyses used 60 cases after casewise deletion. Consequently, the relationship-testing results are based on the complete-case dataset and not the full recorded survey set.

3.3. Data Collection

Data was collected through a structured online questionnaire administered via SurveyMonkey. The questionnaire collected

contextual information about respondents and included a single global item measuring the perceived extent of AI integration in academic quality management systems. The main survey items were closed-ended and aligned with the eight proposed AI QMS model areas, using a seven-point Likert scale ranging from Strongly Disagree to Strongly Agree. Two open-ended reflection questions were also included to allow respondents to comment on the key opportunities and concerns associated with integrating AI into academic quality management.

The online format was suited to the study because the target respondents were professionally and geographically dispersed across higher education, quality assurance, technology and education-associated settings. It also facilitated anonymous completion, which was imperative given the nature of the questions on institutional readiness, governance, assessment practices, quality systems and AI-related capability, all of which may involve sensitive perceptions of institutional practice. Participation was voluntary, and the first page of the questionnaire explained the purpose of the study, the anonymous nature of the survey and how the data would be handled in accordance with the Protection of Personal Information Act, 2013. Participants had to provide consent before commencing with the questionnaire.

3.4. Measurement Instrument

The questionnaire was developed from the conceptual and qualitative phases of the full doctoral study. It was first organised around eight AI QMS areas: Strategic Planning, AI Literacy and Competency Development, Ethical Considerations and Data Privacy, AI in Teaching and Learning, Assessment and Evaluation, AI in Research and Big Data Analytics, Environmental Impact of AI Technologies and Interdisciplinary Collaboration. The closed-ended items used a seven-point Likert scale ranging from Strongly Disagree to Strongly Agree, allowing respondents to indicate their levels of agreement with statements about AI integration into academic quality management. The analysis is based on the revised factor structure that emerged from the validation phase, which exposed that the original questionnaire structure could not be carried forward unchanged. Some items were removed, and some constructs were narrowed to better reflect the empirical behaviour of the data. The outcome variable was AI_QMS, measured by a single global item asking respondents to indicate the overall extent to which AI is integrated into academic quality management systems. Since AI_QMS was measured with a single item, it is interpreted as an overall perception of AI QMS integration rather than as a fully developed multi-item latent construct, in line with Allen et al. (2022) position that single-item measures can be appropriate when an overall judgement is required, provided their limits are acknowledged.

3.5. Retained Factor Structure Used in this Article

The retained factor structure used in this analysis was drawn from the validation phase of the study (Bosch, 2026). In that study, the proposed AI QMS constructs were examined using the KMO and Bartlett tests, exploratory factor analysis, factor-loading assessment, and Cronbach's alpha reliability testing. These results confirmed that the constructs were suitable for factor analysis and that the retained factors confirmed acceptable to excellent reliability. The original model was thus retained and advanced before being applied further.

The final structure retained eight AI QMS areas. Three constructs were carried forward without item removal: Strategic Planning, Ethical Considerations and Data Privacy, and Environmental Impact of AI Technologies. The remaining five constructs were retained in adjusted form. AI Literacy and Competency Development retained AL1, AL3, AL4, AL5 and AL6, while AL2 and AL7 were removed or separated from the final factor. AI in Teaching and Learning retained TL1, TL2 and TL3, with TL4 and TL5 removed from the main factor. Assessment and Evaluation retained AE2, AE3, AE4 and AE5, while AE1 was removed because it did not align sufficiently with the retained assessment factor. Research Governance and Responsible AI Use was narrowed to RB4, RB5 and RB6. Interdisciplinary Collaboration retained IC1, IC2, IC3 and IC5, while IC4 was removed from the final factor.

This retained structure provides the basis for the measurement in the present analysis. The relationship testing and interpretation are therefore based on the empirical model, rather than on the original structure in which all proposed items were still included.

3.6. Data Analysis

The AI QMS integration model provided the basis for the analysis. Its eight retained factors were considered in relation to AI_QMS, the global measure of respondents' perceived extent of AI integration into academic quality management. Rather than relying on a single statistical procedure, the analysis brought together PLS-SEM, Pearson correlations, and multiple regression to examine the relationships from different angles. PLS-SEM examined the eight factors simultaneously and provided estimates of the structural paths to AI_QMS. The analysis also assessed the measurement performance of the constructs through Cronbach's alpha, rhoA, composite reliability and average variance extracted. Bootstrapping was used to test the statistical significance of the paths. Pearson correlations provided a different view by showing how each factor related to AI_QMS before the influence of the other predictors was accounted for. They also revealed the extent of overlap among the factors themselves. This was relevant because strategic planning, AI literacy, ethics, teaching and learning, assessment, research governance, sustainability and interdisciplinary collaboration are connected aspects of institutional practice rather than separate institutional functions. Multiple regression was then used to examine the contribution of each factor while the remaining predictors were held constant. This made it possible to identify which factors explained unique variation in AI_QMS. The regression results were interpreted alongside the PLS-SEM and correlation findings, with attention to points of agreement and difference between the analyses. Field (2024) provides the methodological basis for the regression procedures and their interpretation.

The analyses were used to map the current pattern of AI integration into academic quality management and to highlight which factors were most clearly related to AI_QMS, which factors showed evidence that differed across methods, and which relationships remain difficult to interpret.

3.7. Methodological Cautions

Interpretation was influenced by both the measurement of AI_QMS and the overlap among the retained factors, as AI_QMS was captured by a single global item reflecting respondents' overall perception of the extent to which AI is integrated into academic quality management systems. Although this provided a suitable outcome measure, it did not offer the same depth of measurement as a multi-item construct, and the results are therefore understood as relationships with the broader perception of AI QMS integration.

Strategic planning, AI literacy, ethics, teaching and learning, assessment, research governance, sustainability and collaboration do not operate in isolation, and the correlation analysis confirmed that several predictors shared substantial variance, which is vital when understanding the regression coefficients, because the direction and size of a coefficient may change once the other factors are considered simultaneously.

The PLS-SEM measurement results introduced a further consideration, since paths involving constructs with weaker reliability and convergent-validity indicators had to be interpreted guardedly. These considerations informed the comparison of the PLS-SEM, correlation and regression findings and placed limits on the conclusions drawn from individual coefficients.

4. RESULTS

4.1. Overview of the Analysis

The outcomes are presented in line with the study's two objectives, beginning with the relationships between the retained AI QMS factors and respondents' overall perceptions of AI integration into academic quality management systems, and then turning to how existing practice is exhibited across the eight retained areas. These comprise Strategic Planning, AI Literacy and Competency Development, Ethical Considerations and Data Privacy, AI in Teaching and Learning, Assessment and Evaluation, Research Governance and Responsible AI Use, Environmental Impact of AI Technologies and Interdisciplinary Collaboration, which together provide the structure for researching AI QMS integration in South African private higher education.

PLS-SEM considers the eight factors simultaneously and tests the significance of their paths to AI_QMS, and the Correlation analysis shows how each factor relates to AI_QMS before the influence of the remaining factors is considered, while also divulging the degree of overlap among the predictors. Multiple regression then approximates the contribution of each factor when all eight are considered within the same model and is supplemented by Construct-level descriptive statistics to present how respondents rated existing institutional practice across the retained areas.

4.2. PLS-SEM Model Behaviour

PLS-SEM was used to examine the relationships between the eight retained factors and AI_QMS. The model explained 30.7% of the variance in AI_QMS, while the adjusted R^2 was 19.1%. The difference between these values reflects the number of predictors included relative to the available sample size and suggests that the model has modest explanatory power. Research Governance and Responsible AI Use was the only factor with a statistically significant path to AI_QMS. Its positive coefficient was $\beta = 0.387$, with $t = 2.315$ and $P = 0.036$. The 95% confidence interval ranged from 0.027 to 0.694 and did not include zero, providing further support for this relationship (Table 2).

None of the remaining paths reached statistical significance. AI Literacy and Competency Development, AI in Teaching and Learning, Environmental Impact of AI Technologies and Interdisciplinary Collaboration recorded positive coefficients, but their confidence intervals included zero. Strategic Planning produced a coefficient close to zero, while Assessment and Evaluation and Ethical Considerations and Data Privacy recorded small negative coefficients. These results do not show that the factors are irrelevant to academic quality management; rather, they did not demonstrate independent structural relationships with AI_QMS in this PLS-SEM model.

The construct-level measurement results were acceptable for Research Governance and Responsible AI Use, Strategic Planning, AI in Teaching and Learning, Ethical Considerations and Data Privacy, Environmental Impact of AI Technologies and Interdisciplinary Collaboration. For these constructs, Cronbach's alpha, rhoA and composite reliability exceeded 0.70, while average variance extracted exceeded 0.50.

AI Literacy and Competency Development, and Assessment and Evaluation did not meet the same criteria. Although their Cronbach alpha values were acceptable, their rhoA, composite reliability and average variance extracted values were below the required thresholds. The negative rhoA values also indicate instability in the way their indicators operated within the PLS-SEM model (Table 3).

The PLS-SEM findings provide partial support for the applied model. Research Governance and Responsible AI Use showed a clear positive relationship with AI_QMS, while the other paths were not statistically supported. The results for AI Literacy and Competency Development, and Assessment and Evaluation require caution because weaknesses in their measurement performance limit the confidence with which their structural coefficients can be interpreted.

4.3. Correlation Analysis

Table 4 shows the results of the Pearson correlation analysis was used to examine the relationships between AI_QMS and each retained factor. The analysis was based on 60 complete cases after casewise deletion of missing data.

Four factors were positively and significantly related to AI_QMS ($P \leq 0.05$). Research Governance and Responsible AI Use recorded the largest correlation ($r = 0.4358$, $P = 0.001$), followed by Interdisciplinary Collaboration ($r = 0.3483$, $P = 0.006$); Strategic Planning ($r = 0.2931$, $P = 0.023$); and Environmental Impact of AI Technologies ($r = 0.2849$, $P = 0.027$).

No significant relationship was found for Ethical Considerations and Data Privacy, $r = 0.1292$, $P = 0.325$; AI in Teaching and Learning ($r = 0.1198$, $P = 0.362$); AI Literacy and Competency Development ($r = 0.0424$, $P = 0.748$); or Assessment and Evaluation ($r = 0.0369$, $P = 0.780$).

Table 2: Bootstrapped PLS-SEM path coefficients

Construct	Original Est.	bootstrap mean	Bootstrap SD	T statistics	2.5% CI	97.5% CI	Bootstrap P-value
Research governance and responsible AI use	0.386873067	0.35098637	0.1670982	2.315243564	0.02659779	0.6942991	0.0360
Assessment and evaluation	−0.054691633	−0.10500819	0.2577813	−0.212162884	−0.56021054	0.4253286	0.6780
Strategic planning	0.001044519	0.32262426	0.2361812	0.004422531	−0.19754206	0.7549109	0.1776
AI literacy and competency development	0.206188373	−0.29076880	0.2822358	0.730553510	−0.78708173	0.2946954	0.3304
AI in teaching and learning	0.109850196	0.12088930	0.1687637	0.650911424	−0.26106499	0.4126686	0.4308
Ethical considerations and data privacy	−0.043501191	−0.01947430	0.2045420	−0.212676107	−0.45521966	0.3571316	0.9472
Environmental impact of AI technologies	0.104968897	0.05096734	0.1410981	0.743942861	−0.24163306	0.3263651	0.6888
Interdisciplinary collaboration	0.124277249	0.12266616	0.1837702	0.676264407	−0.25531132	0.4756600	0.4780

Model R^2=0.307; adjusted R^2=0.191

Considered separately, Research Governance and Responsible AI Use showed the clearest relationship with respondents' overall perception of AI QMS integration. Interdisciplinary Collaboration, Strategic Planning and Environmental Impact were also related to AI_QMS, although their correlations were smaller. Teaching and Learning were not significant in the correlation analysis, but became significant once the other predictors were included in the regression model.

The matrix also showed considerable overlap among several predictors. Strategic Planning was strongly correlated with AI Literacy and Competency Development (r = 0.7289) and showed moderate-to-strong relationships with Ethical Considerations (r = 0.6286), Data Privacy (r = 0.6080), and Assessment and Evaluation (r = 0.6080). Its relationships with Research Governance and Responsible AI Use (r = 0.4617) and Interdisciplinary Collaboration (r = 0.4409) were moderate. Ethical Considerations and Data Privacy was also related to Assessment and Evaluation (r = 0.6419), AI Literacy and Competency Development (r = 0.5949), and Interdisciplinary Collaboration (r = 0.4891). A further substantial relationship occurred between Research Governance and Responsible AI Use and Interdisciplinary Collaboration (r = 0.6191).

These relationships confirm that the retained factors do not operate in isolation as institutional functions. Their overlap is important when interpreting the regression results because each coefficient represents the contribution of a factor after accounting for the variance shared with the other predictors. This may help explain why AI Literacy and Competency Development and Assessment and Evaluation showed negligible relationships with AI_QMS but produced significant negative coefficients in the regression model.

4.4. Multiple Regression Analysis

Multiple regression was used to examine the contribution of each retained factor to AI_QMS after accounting for the other predictors (Table 5). The model was statistically significant, $F(8,51) = 4.2002$, $P < 0.001$, and explained 39.7% of the variance in AI_QMS. The adjusted R^2 was 30.3%, indicating moderate explanatory value within this exploratory, perception-based study.

Table 3: PLS-SEM reliability and convergent validity results

Construct	Cronbach's alpha	rhoA	rhoC	AVE
RB	0.787	0.807	0.874	0.698
AE	0.752	−0.656	0.560	0.293
SP	0.875	0.939	0.902	0.651
AL	0.862	−1.517	0.119	0.116
TL	0.836	0.889	0.898	0.745
ED	0.941	0.738	0.934	0.745
EI	0.934	0.963	0.952	0.833
IC	0.777	0.795	0.854	0.595

Table 4: Pearson correlations with AI_QMS

Factor	r with AI_QMS	P-value	Interpretation
Research governance and responsible AI use	0.4358	0.001	Significant positive
Interdisciplinary collaboration	0.3483	0.006	Significant positive
Strategic planning	0.2931	0.023	Significant positive
Environmental impact of AI technologies	0.2849	0.027	Significant positive
Ethical considerations and data privacy	0.1292	0.325	Not significant
AI in teaching and learning	0.1198	0.362	Not significant
AI literacy and competency development	0.0424	0.748	Not significant
Assessment and evaluation	0.0369	0.780	Not significant

Table 5: Multiple regression results

Predictor	Standardised beta	t-value	P-value
Strategic planning	0.5279	2.8902	0.0056
AI literacy and competency development	−0.3653	−2.1611	0.0354
Ethical considerations and data privacy	−0.0814	−0.4793	0.6338
AI in teaching and learning	0.3054	2.4087	0.0197
Assessment and evaluation	−0.3897	−2.2833	0.0266
Research governance and responsible AI use	0.4560	2.7934	0.0073
Environmental impact of AI technologies	0.0240	0.1859	0.8532
Interdisciplinary collaboration	0.1168	0.7396	0.4629

Three factors made significant positive contributions to AI_QMS. Strategic Planning recorded the largest standardised coefficient (β = 0.5279, P = 0.0056), followed by Research Governance and Responsible AI Use (β = 0.4560, P = 0.0073). AI in Teaching and Learning also contributed positively (β = 0.3054, P = 0.0197).

A different pattern emerged for AI Literacy and Competency Development (β = −0.3653, P = 0.0354) and Assessment and Evaluation (β = −0.3897, P = 0.0266). Neither factor was significantly correlated with AI_QMS when examined on its own, yet both became significant and negative once the remaining predictors were included. Since these factors also shared substantial variance with several other predictors, the change may reflect suppression or the redistribution of shared variance within the full regression model. It should not be interpreted as evidence that greater AI literacy or stronger assessment practice reduces AI QMS integration.

The partial and semi-partial correlations provide further detail on the contribution that remained after accounting for the other predictors. Strategic Planning recorded a partial correlation of 0.3751 and a semi-partial correlation of 0.3142. For Research Governance and Responsible AI Use, the corresponding values were 0.3643 and 0.3037, while AI in Teaching and Learning recorded 0.3196 and 0.2619.

The negative relationships also remained for AI Literacy and Competency Development, with a partial correlation of −0.2896 and a semi-partial correlation of −0.2350, and for Assessment and Evaluation, with corresponding values of −0.3045 and −0.2482. Ethical Considerations and Data Privacy, Environmental Impact of AI Technologies and Interdisciplinary Collaboration did not make statistically significant contributions once all eight predictors were considered together.

4.5. Relationship-testing Summary

The analyses provide partial support for the relationships proposed in the AI QMS model. Research Governance and Responsible AI Use produced the clearest and most consistent result across the analyses. Strategic Planning and AI in Teaching and Learning showed support that varied by method, while AI Literacy and Competency Development and Assessment and Evaluation require cautious interpretation because their negative regression coefficients were not supported by the correlation or PLS-SEM findings and were affected by measurement concerns. Ethical Considerations and Data Privacy, Environmental Impact of AI Technologies and Interdisciplinary Collaboration did not explain additional variation in AI_QMS once the other predictors were considered.

4.6. Hypothesis Decisions

The general hypothesis received partial support. As shown in Table 6, the multiple regression model was statistically significant, but only five of the eight factor-level relationships reached significance. Three were positive, while AI Literacy and Competency Development and Assessment and Evaluation were significant in a negative direction.

The decisions in Table 6 reflect the relationships found in the full regression model. Research Governance and Responsible AI Use was also supported by the PLS-SEM analysis, while the PLS paths for the other factors were not significant. The negative regression results for AI Literacy and Competency Development and Assessment and Evaluation require caution because neither factor was significantly correlated with AI_QMS and both showed measurement concerns in the PLS-SEM analysis.

Table 6: Hypothesis decisions

Hypothesis	Regression result	Decision
$H_{1.1}$ Strategic planning is significantly related to AI_QMS	β=0.5279, P=0.0056	Supported
$H_{1.2}$ AI literacy and competency development is significantly related to AI_QMS	β=−0.3653, P=0.0354	Supported, negative direction
$H_{1.3}$ Ethical considerations and data privacy is significantly related to AI_QMS	β=−0.0814, P=0.6338	Not supported
$H_{1.4}$ AI in teaching and learning is significantly related to AI_QMS	β=0.3054, P=0.0197	Supported
$H_{1.5}$ Assessment and evaluation is significantly related to AI_QMS	β=−0.3897, P=0.0266	Supported, negative direction
$H_{1.6}$ Research governance and responsible AI use is significantly related to AI_QMS	β=0.4560, P=0.0073	Supported
$H_{1.7}$ Environmental impact of AI technologies is significantly related to AI_QMS	β=0.0240, P=0.8532	Not supported
$H_{1.8}$ Interdisciplinary collaboration is significantly related to AI_QMS	β=0.1168, P=0.4629	Not supported

The non-significant regression results do not mean that Ethical Considerations and Data Privacy, Environmental Impact of AI Technologies or Interdisciplinary Collaboration have no place in the polished model. They show that these factors did not account for additional variation in AI_QMS once the other predictors were considered.

4.7. Descriptive Measurement of the Retained AI QMS Areas

The second objective considered how respondents rated current practice across the eight retained AI QMS areas. Construct-level descriptive statistics were used for this purpose, providing a separate view from the relationship analyses reported above.

Table 7 shows that AI in Teaching and Learning received the highest mean rating (M = 5.2582, SD = 1.2814), followed by Research Governance and Responsible AI Use, (M = 5.0000, SD = 1.1764) and Assessment and Evaluation (M = 4.9743, SD = 1.0704). Ethical Considerations and Data Privacy recorded a mean of 4.9101 (SD = 1.4783), while Interdisciplinary Collaboration recorded 4.7351 (SD = 1.1222). The mean for Strategic Planning was 4.6000 (SD = 1.3963), and AI Literacy and Competency Development recorded 4.5391 (SD = 1.2416). Environmental Impact of AI Technologies received the lowest mean rating, (M = 3.8015, SD = 1.4336).

The descriptive and relationship results do not produce identical rankings. Teaching and Learning received the highest mean rating and made a significant positive contribution in the regression model, but it was not significantly related to AI_QMS in either the correlation or PLS-SEM analysis. Research Governance and

Table 7: Descriptive statistics and normality assessment of retained AI QMS constructs

Construct	Mean	Minimum	Maximum	Standard deviation	Skewness	Kurtosis
Strategic planning	4.6000	1.00	7.00	1.3963	−0.7641	0.2241
AI literacy and competency development	4.5391	1.00	6.60	1.2416	−0.6728	0.1177
Ethical considerations and data privacy	4.9101	1.00	7.00	1.4783	−0.7704	0.2297
AI in teaching and learning	5.2582	1.00	7.00	1.2814	−0.7561	0.6987
Assessment and evaluation	4.9743	1.00	7.00	1.0704	−0.8063	1.9076
Research governance and responsible AI use	5.0000	2.00	7.00	1.1764	−0.2004	−0.5784
Environmental impact of AI technologies	3.8015	1.00	7.00	1.4336	0.0555	−0.5777
Interdisciplinary collaboration	4.7351	2.00	7.00	1.1222	−0.3253	−0.0186

Responsible AI Use produced a more consistent pattern: it received one of the highest mean ratings, had the largest correlation with AI_QMS, contributed positively to the regression model and was the only significant PLS-SEM path. Strategic Planning occupied a different position. Its mean was lower than those of Teaching and Learning, Research Governance, Assessment and Ethical Considerations and Data Privacy, yet it recorded the largest positive coefficient in the regression model. Respondents did not rate it as the most established area of current practice, but variation in Strategic Planning was strongly associated with variation in AI_QMS after accounting for the other predictors (Table 7).

Assessment and Evaluation received a relatively high mean rating, although its other results were less consistent. It was not significantly correlated with AI_QMS, its PLS-SEM path was not significant, and its regression coefficient was negative. The PLS-SEM measurement results also raised concerns about its rhoA, composite reliability and average variance extracted. The mean, therefore, suggests that respondents recognised activity in assessment, but it should not be taken as evidence that the construct performed strongly across the full analysis.

AI Literacy and Competency Development also require caution. Its mean was above the scale midpoint, but it showed no significant relationship with AI_QMS in either the correlation or PLS-SEM analysis and produced a negative coefficient in the regression model. Its PLS-SEM measurement results were particularly weak. The descriptive rating can therefore be reported as evidence of respondents' perceptions, but it does not resolve the uncertainty surrounding the construct's measurement and relationship with AI_QMS.

Environmental Impact of AI Technologies received the lowest mean rating and was the only construct with a mean below the scale midpoint of four. It was positively correlated with AI_QMS but did not contribute significantly to either the regression or PLS-SEM analysis. It is therefore implied that environmental considerations were less visible in respondents' accounts of current AI QMS practice, although their relationship with the wider model may overlap with other institutional factors.

Skewness values ranged from −0.8063 to 0.0555, while kurtosis ranged from −0.5784 to 1.9076. These values do not indicate severe departures from normality at the construct level. Most constructs were negatively skewed, showing that responses tended towards the agreement end of the scale. Environmental Impact of AI Technologies was the exception, with near-zero skewness and a lower mean than the remaining constructs.

4.8. Measuring Current AI QMS Integration against the Refined Model

The combined results do not point to a single, uniform pattern of AI QMS integration. The relationships differed across the three analyses, and the descriptive ratings did not always align with the structural findings. This indicates that visible activity in an area, such as teaching, assessment or policy development, should not automatically be interpreted as evidence that AI has been fully integrated into academic quality management systems. The refined model therefore provides a differentiated view of current AI QMS practice. Research Governance and Responsible AI Use emerged as the most consistent relationship, while Strategic Planning and AI in Teaching and Learning showed method-dependent support. AI Literacy and Competency Development and Assessment and Evaluation require more cautious interpretation because their regression results were not supported in the same way by the correlation and PLS-SEM findings. Ethical Considerations and Data Privacy, Environmental Impact of AI Technologies and Interdisciplinary Collaboration remained relevant to the model but did not independently explain AI_QMS in the multivariable analyses. The practical value of the model lies in the way it brings these differences into view. It shows where AI integration appears more strongly embedded, where relationships depend on other institutional conditions, and where the measurement structure requires further attention.

5. DISCUSSION

The AI QMS model produced different results depending on how the relationships were examined. This mixed behaviour should be read as part of the finding, not merely as a complication in the analysis. The retained factors did not operate as equal routes to AI_QMS, the outcome variable measuring respondents' overall perceived extent of AI integration into academic quality management systems. Instead, they pointed to different degrees of institutionalisation. Teaching activity, assessment responses, training and research use may be visible as practice, while governance, strategy and accountability become meaningful when AI is built into the processes through which institutions plan programmes, review standards, manage risk and produce evidence for quality decisions. AI may therefore be widely used without being fully absorbed into the academic quality cycle. The model's value lies in distinguishing visible AI activity from institutionally embedded AI integration.

5.1. Governance and Strategy as Institutional Anchors

Research Governance and Responsible AI Use provide the clearest point of agreement in the model. It recorded the strongest and

most consistent relationship with AI_QMS and was the only factor supported across the correlation, regression and PLS-SEM analyses. Strategic Planning also showed a meaningful relationship with AI_QMS, although its pattern was less stable. Read together, these findings indicate that AI integration into academic quality management is recognised most clearly where AI is connected to institutional direction, research governance, policy, verification, responsible data use and human accountability.

Oncioiu and Bularca (2025) provide a useful comparison because their model placed AI governance within institutional knowledge practices. Collaborative knowledge dynamics strongly predicted AI governance ($\beta = 0.457$, $P < 0.001$), while a knowledge-based educational orientation also made a significant contribution ($\beta = 0.393$, $P < 0.001$). Although their study treated governance as an outcome, while the present study treats Research Governance and Responsible AI Use as a predictor of AI_QMS, both studies point to the same institutional logic. Governance becomes stronger when it is linked to knowledge practices, collaboration and academic judgement, rather than restricted to policy statements. Shrivastava (2025) supports this interpretation from an individual acceptance perspective, finding that sociolegal factors, including AI regulation and trust in governance, were positively related to acceptance of generative AI ($\beta = 0.48$, $P < 0.01$) and negatively related to resistance ($\beta = -0.36$, $P < 0.01$).

Alqurni (2026), however, found that institutional policy support strongly predicted digital infrastructure ($\beta = 0.502$, $P < 0.001$), while its direct path to sustainable adoption was not significant. Governance therefore mattered indirectly through infrastructure rather than as an independent predictor of adoption. This contrast is important because it shows that governance behaves differently depending on what is being measured. Where AI is examined as technology adoption, policy may be experienced through access, infrastructure or implementation support. Where AI is examined through academic quality management, governance is closer to the outcome because verification, disclosure, research ethics, data responsibility and human oversight form part of the institutional system being assessed.

The strategic-planning results should be interpreted in the same way. Ul Haq and Mohd Suki (2024) found that leadership vision predicted AI adoption ($\beta = 0.362$, $P < 0.001$), while change-management capability made a stronger contribution ($\beta = 0.475$, $P < 0.001$), although leadership vision did not improve firm performance indirectly through adoption. Nguyen et al. (2026) similarly found that top-management commitment, support and organisational flexibility contributed to AI adoption intention, whereas leadership vision alone was not significant. Korzyński et al. (2024) located the effect of top management support in an indirect pathway through trust, with support predicting trust in AI ($\beta = 0.389$, $P < 0.001$), and trust subsequently predicting actual use ($\beta = 0.353$, $P < 0.001$). These studies indicate that strategy becomes consequential only when it is converted into implementation conditions.

In the South African private higher education sector, this is not merely a management preference. The CHE's QAF and programme accreditation requirements place emphasis on credible and appropriately governed academic provision; the DHET institutional types policy frames institutional recognition; the NQF level descriptors guide qualification coherence and expected learning achievement; and POPIA regulates the responsible processing of personal information (DHET, 2025). AI use in research, teaching and assessment therefore cannot remain an informal academic convenience. The institution must still be able to show how scholarly judgement was exercised, how outputs were verified, how data were protected, how programme quality was maintained and who remained accountable for academic work. Research Governance and Responsible AI Use appears more stable than the other factors because it is the area where AI integration is most clearly connected to these existing quality, accreditation and accountability responsibilities. Strategic Planning matters because it coordinates those responsibilities, but its effect becomes visible only when strategy enters programme review, assessment policy, staff development, research governance, procurement, data protection and internal quality review.

5.2. Visible Academic Practice and Quality-assured Integration

AI in Teaching and Learning was the most highly rated construct and was positively supported in the regression model, but it was not consistently related to AI_QMS across the correlation and PLS-SEM analyses. Assessment and Evaluation also showed considerable reported activity, yet its negative regression coefficient and weak PLS-SEM measurement results do not support a simple conclusion about maturity. These results should be read together because both teaching and assessment are areas where AI may be highly visible before it is fully absorbed into quality assurance processes.

Dong et al. (2026) reported a positive coefficient of similar magnitude in their study of generative AI-based learning analytics and student engagement, where AI-supported learning analytics significantly predicted engagement ($\beta = 0.317$, $P < 0.001$). Their findings support the educational value of AI when it is embedded in intentional learning design and supported by cognitive, social and teaching presence. Baig and Yadegaridehkordi (2025), however, found that the contribution of generative AI depended on the outcome being tested. Performance expectancy predicted continued intention to use GenAI, but not staff satisfaction, which was shaped more strongly by expectation confirmation, effort expectancy, security, privacy and ethical considerations. Abbas et al. (2024) provide an important qualification, finding that frequent academic use of ChatGPT predicted procrastination ($\beta = 0.309$, $P < 0.001$) and was negatively associated with objectively measured academic performance.

These studies prevent teaching activity from being interpreted as automatic quality integration. AI in Teaching and Learning may contribute to perceived AI integration into academic quality management when it is tied to intentional design, lecturer guidance, student support and programme-level review. It may also remain a visible but weakly governed practice where use is informal, student-driven or unevenly connected to curriculum and assessment decisions. Teaching innovation often moves quickly because institutions respond to student expectations, online learning demands and competitive pressures, whereas

quality assurance moves through slower forms of evidence, including curriculum alignment, moderation, assessment validity, staff capability, student support and programme review. The differentiating issue for AI_QMS is therefore not whether AI is being used in teaching, but whether such use has been absorbed into the processes used to review and protect programme quality.

Assessment makes this distinction sharper. Scarfe et al. (2024) demonstrated the scale of institutional exposure in a blind-examination study where 94% of AI-generated submissions went undetected by markers. Torres-Diaz et al. (2025) found that wider knowledge of AI tools was associated with reduced odds of self-reported plagiarism (OR = 0.911, $P < 0.001$), while trust in ChatGPT-generated information increased the odds (OR = 1.176, $P < 0.001$). Yusuf et al. (2024) also showed that concerns about cheating, plagiarism and regulation were substantial but not uniform across respondents. These findings support the argument that assessment policy, academic integrity, AI knowledge, disclosure, grading, redesign and detection should not be treated as interchangeable indicators of one institutional condition.

The deeper quality question is whether assessment still produces credible evidence of student competence in relation to the relevant NQF level, programme outcomes and graduate attributes. An assessment policy may mention AI, and a detection tool may be available, but that does not necessarily show that assessment tasks, moderation processes, marking standards and evidence of learning remain fit for purpose. The present findings do not establish that Assessment and Evaluation weaken AI integration into academic quality management systems. They indicate that the construct may be too broad for the way assessment is currently being disrupted and may require separation into assessment policy, assessment redesign, AI-use declarations, academic integrity procedures, moderation, grading validity and detection practices.

5.3. Capability, Ethics and Responsible Institutional Practice

AI Literacy and Competency Development and Ethical Considerations and Data Privacy behaved differently in the model, but both point to the conditions under which AI use becomes academically defensible. AI Literacy and Competency Development did not perform consistently and cannot be interpreted as having a simple negative effect on AI integration into academic quality management. Ethical Considerations and Data Privacy were recognised by respondents and performed adequately in the measurement results, but did not distinguish levels of AI_QMS. This suggests that literacy, ethics and privacy may not operate as straightforward predictors. They may instead form part of the capability and responsibility base that makes AI use academically acceptable.

Bećirović et al. (2025) provide empirical support for this interpretation. Their model separated technological understanding, practical application and critical appraisal, showing that these dimensions do not move in a single direction. Practical application had a strong positive effect on AI self-efficacy ($\beta = 0.705$, $P < 0.001$), while critical appraisal predicted lower self-efficacy ($\beta = -0.348$, $P = 0.016$) and lower perceived output quality ($\beta = -0.571$, $P = 0.002$). These findings are relevant because practical skill, confidence and critical awareness cannot be assumed to develop together. Greater awareness of privacy, legal, ethical and reliability concerns may lower confidence even while practical competence improves.

The Ecuadorian findings from Torres-Diaz et al. (2025) add a further qualification, since wider knowledge of AI tools reduced plagiarism risk, while trust in ChatGPT-generated information increased it. Knowledge and confidence therefore produced different consequences. AI literacy in private higher education cannot be reduced to tool training. It must include the ability to verify outputs, protect sensitive data, recognise unreliable content, disclose AI assistance and apply different rules across disciplines, assessment types and qualification levels. The present findings therefore do not weaken the case for AI literacy. They show that AI Literacy and Competency Development require sharper conceptualisation and further instrument refinement.

Ethics and privacy appear to operate differently. Weis et al. (2026) reported that privacy was positively associated with actual generative AI use but narrowly missed statistical significance ($B = 0.12$, $P = 0.058$), while trust was unrelated to behavioural intention and actual use. Zhang et al. (2025) found a more conditional relationship, where ethical concerns did not operate as a simple direct predictor of adoption but altered relationships among perceived utility, social influence, perceived risk and the adoption of AI-based data-analysis tools. These studies support the interpretation that ethics and privacy may shape acceptable practice without independently explaining perceived integration.

In the present model, Ethical Considerations and Data Privacy appear less as predictors of higher perceived integration and more as minimum conditions for lawful and defensible AI use. POPIA and institutional governance expectations already frame data protection as a minimum requirement, and respondents may therefore not interpret ethics and privacy as signs of advanced integration. Another possible reading is that ethics and privacy remain too abstract in some institutional settings. Respondents may agree that they matter but may not yet see them translated into specific AI decisions about platforms, student data, assessment submissions, research information or vendor systems. Either way, the non-significant result should not be read as evidence that ethics and privacy are marginal. It indicates that these areas are foundational, and in some cases insufficiently operationalised, rather than unimportant.

5.4. Weakly Embedded and Indirect Dimensions of Integration

Environmental Impact of AI Technologies and Interdisciplinary Collaboration were positively related to AI_QMS in the correlation analysis, but neither factor remained significant in the regression or PLS-SEM results. These two factors should not be dismissed, but they appear to represent weaker or more indirect forms of integration. Environmental Impact was the least visible area in respondents' ratings, while Interdisciplinary Collaboration overlapped strongly with Research Governance and Responsible AI Use. Their behaviour suggests that sustainability and

collaboration may matter most when they are built into institutional decisions rather than treated as separate indicators of integration.

Alqurni (2026) found that Energy-Efficient AI Systems made a small but statistically significant contribution to sustainable AI-Metaverse adoption ($\beta = 0.148$, $P = 0.042$), while readiness and access operated through student acceptance. Chandran et al. (2026), working in the banking sector, found that Green AI adoption predicted sustainability outcomes ($\beta = 0.446$, $P < 0.001$), with infrastructure and investment among the strongest adoption predictors. These studies suggest that environmental impact becomes more visible when sustainability is connected to identifiable decisions such as infrastructure, investment, procurement and adoption outcomes. In the present study, Environmental Impact did not retain an independent relationship with AI_QMS. Sustainability may therefore not yet have been translated into the technology approval, vendor-selection and quality review processes through which institutions manage AI. It may also be less visible because many institutions rely on external platforms and cloud-based services, where the environmental cost is displaced to vendors and data centres rather than appearing within everyday academic quality processes.

Interdisciplinary Collaboration followed a related, although not identical, pattern. Oncioiu and Bularca (2025) located collaboration within an institutional sequence where Collaborative Knowledge Dynamics predicted AI Governance ($\beta = 0.457$, $P < 0.001$) and Ethically Oriented Organisational Culture ($\beta = 0.555$, $P < 0.001$), while governance then contributed to legal and ethical AI literacy. Collaboration did not appear as the final outcome in their model but helped shape governance and organisational culture. Yan and Tang (2025) approached collaboration through designed learning activity and found that AIGC-assisted teaching improved interdisciplinary communication by 23.6%, with gains strongest where tools were embedded in structured activities requiring students to translate concepts across disciplinary boundaries.

Those outcomes are not directly equivalent to AI_QMS, but they show that collaboration produces clearer effects when it is built into defined processes. In the present study, Interdisciplinary Collaboration appears to be intertwined with Research Governance and other institutional factors. Its contribution may therefore become more evident through shared review, knowledge exchange and joint responsibility than through a separate direct path to AI_QMS. Collaboration remains important because AI-related decisions cut across academic leadership, quality assurance, information technology, research support, compliance, teaching, assessment and student support. Its value may lie in coordinating these functions rather than in operating as an independent predictor.

Overall, the findings are partly confirmatory, partly qualifying and partly extending. They confirm studies that locate governance, trust, strategy, capability and responsible use as important conditions for AI adoption and implementation. They qualify adoption-based research by showing that teaching activity, strategy, ethics, collaboration and sustainability do not behave in the same way when the outcome is the AI_QMS variable rather than technology use or adoption intention. They extend the literature by showing that, in academic quality management, AI becomes institutionally meaningful when it can be connected to evidence, accountability, programme quality, assessment credibility, qualification expectations and defensible academic judgement.

For the South African private higher education sector, the central implication is that AI integration does not advance evenly across governance, pedagogy, assessment, capability, ethics, sustainability and collaboration. Activity in one area cannot be used as evidence that the wider academic quality management system has developed to the same level. The AI QMS model therefore contributes by distinguishing visible AI use from institutionally embedded AI integration. It shows where AI has begun to enter the systems through which academic quality is governed, and where it remains a set of dispersed practices requiring clearer policy, stronger evidence, sharper measurement and more deliberate institutional coordination.

5.5. Contribution of the Article

This article advances the AIQMS framework from exploratory validation to empirical application by testing how retained factors relate to AI integration using multiple statistical methods (PLS-SEM, correlation, regression, and descriptive analysis). Its key contribution lies in demonstrating that factors behave differently depending on the analytical approach, highlighting that measurement validity does not necessarily translate into consistent explanatory power. The findings show that Research Governance and Responsible AI Use is the only factor consistently supported across all methods, while others (such as Strategic Planning and Teaching and Learning) show partial or method-dependent significance. This underscores that visible institutional activity does not always equate to a strong multivariable contribution to AI_QMS.

The study also contributes by identifying areas of uncertainty, particularly AI Literacy and Competency Development and Assessment and Evaluation, where inconsistent and weak measurement results suggest the need for further refinement rather than indicating poor institutional performance.

In practical terms, the article offers a structured, multidimensional model for South African private higher education institutions to assess AI integration across key domains without reducing the concept to a single metric. Overall, it provides both empirical insight and applied value by showing where AI integration is most clearly supported, where results vary across methods, and where further measurement development is required.

6. CONCLUSION

This article applies a refined model to assess how artificial intelligence (AI) is integrated into Academic Quality Management Systems (AQMS) in South African private higher education. It moves beyond earlier model validation to examine how key institutional factors relate to perceived AI integration using statistical methods such as PLS-SEM, regression, and correlation analysis. The findings show that Research Governance and

Responsible AI Use are the most consistent and significant factors associated with AI integration across all analyses, highlighting the importance of oversight, accountability, and responsible data use. Strategic Planning and AI in Teaching and Learning also contribute, but their influence varies depending on the statistical method used. Other factors, such as AI Literacy and Assessment, produced inconsistent or unclear results, partly due to measurement limitations, while Ethics, sustainability, and collaboration played a less direct role in explaining AI integration. Overall, the study demonstrates that AI integration in higher education is uneven and multidimensional. It provides a practical framework for institutions to evaluate AI's role in academic quality management, while highlighting areas requiring further development, particularly in measurement and institutional practice alignment.

6.1. Limitations

The study has limitations that should be considered when interpreting the findings. AI_QMS was measured through a single-item indicator capturing respondents' overall perception of AI integration into academic quality management systems. This provided a clear outcome variable but limited the depth with which AI_QMS could be treated as a construct. The sample also constrains generalisability. Although 82 respondents met the consent requirements, only 60 complete cases were available for the relationship-testing analyses. Because participants were purposively selected for their knowledge or professional exposure to AI, academic quality management, higher education or education technology, the findings are informed by relevant stakeholder insight rather than being representative of the broader South African private higher education sector.

Interpretation was further complicated by overlap among key factors such as strategy, literacy, ethics, assessment, research governance and collaboration. Their shared variance may have influenced the regression coefficients, particularly the negative coefficients for AI Literacy and Competency Development and Assessment and Evaluation. These should not be read as evidence that literacy or assessment weakens AI integration, but rather as an indication that individual effects are difficult to isolate within a conceptually connected model. The PLS-SEM results provide only partial support for the proposed model. Research Governance and Responsible AI Use was the only factor with a significant relationship to AI_QMS, while the remaining paths were not statistically supported. Measurement inconsistencies in some constructs, despite acceptable Cronbach's alpha values, also indicate that further instrument refinement is required. Finally, the study relied on stakeholder perceptions rather than independently verified institutional practices. Respondents may not have had complete knowledge of all AI-related policies, systems or practices within their institutions, which introduces the possibility of perception-based bias. These limitations restrict the strength and generalisability of the conclusions, but do not negate the value of the study as an exploratory framework for measuring and refining AI integration into academic quality management systems.

6.2. Future Research

Future research should begin with measurement refinement, particularly by replacing the single-item AI_QMS outcome with a multi-item measure of perceived AI integration into academic quality management systems. AI Literacy and Competency Development and Assessment and Evaluation also require sharper instruments, as their results suggest multidimensional constructs rather than single factors. Once these measures are strengthened, larger and more diverse samples can test whether the AI QMS model behaves differently across institutional roles, provider types and levels of AI maturity. Longitudinal and mixed-method work would further show how AI integration changes over time and whether stakeholder perceptions correspond with actual policies, systems and quality processes.

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