

An Evidence-based Model for Integrating Artificial Intelligence into the Academic Quality Management Systems in South African Private Higher Education Institutions

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Abstract: The purpose of this article is to present the quantitative validation phase of a sequential exploratory mixed-methods study investigating the integration of Artificial Intelligence into Academic Quality Management Systems in South African Private Higher Education Institutions (PHEIs). This phase empirically tests the conceptual model established in the prior phase through literature review and qualitative thematic analysis. The objective is to determine whether the proposed model functions as a robust measurement structure when assessed against actual data, and to refine it where necessary. The research utilised a survey instrument developed around eight principal themes, including AI's role in strategic planning, teaching and learning, ethics, environmental impact, and interdisciplinary collaboration. Survey responses were analysed to assess whether the model's constructs demonstrate statistical coherence, using established reliability and measurement tests. The results indicate that all constructs were appropriate for factor analysis, and the retained factors exhibited satisfactory internal reliability. Three constructs were retained without modification, while five required item-level refinement. The analysis did not confirm the original conceptual model unchanged; instead, it produced a revised AI QMS integration model with an empirically validated measurement structure. This refined model can be applied in subsequent research to assess institutional AI QMS integration and highlight areas for improvement. The study provides an important first-stage empirical refinement of a theory-driven model developed through a preceding qualitative phase. The objective was not to produce a finalised psychometric instrument but to identify which theoretically derived dimensions demonstrate sufficient coherence for future investigation.

Keywords: Artificial Intelligence; Academic Quality Management Systems; Private Higher Education; South Africa; Model Validation; Exploratory Factor Analysis; AI Governance; AI Literacy; Quality Assurance

JEL codes: I23, I28, O33

1. INTRODUCTION

Artificial intelligence (AI) has become increasingly influential in higher education, with recent studies highlighting its potential to improve adaptive learning, administrative efficiency, and data-informed decision-making (Ahmad et al., 2024; Patel & Ragolane, 2024). In the South African private higher education sector, however, integrating AI remains complex, as institutions must address regulatory requirements, ethical considerations,



infrastructure disparities, and localised governance practices (Patel & Ragolane, 2024). While AI can enhance quality assurance and operational efficiency, its adoption also raises concerns about institutional readiness, stakeholder digital literacy, data privacy, and preserving academic standards (Nguyen et al., 2023; Mbonye et al., 2024).

This study builds on prior research that established a foundation for responsible AI integration in private higher education. Previous phases combined literature review with insights from stakeholders actively engaged in the sector. This approach identified several key themes, including strategic alignment, skills development, ethical governance, pedagogical application, assessment, research integrity, environmental sustainability, and interdisciplinary collaboration. These elements form the conceptual basis for the model evaluated in this article.

This aspect of the study does not reiterate the qualitative thematic findings of earlier work. Instead, it uses the previously developed model as a starting point to examine whether its proposed constructs remain a valid measurement structure. Empirical validation is essential, as theoretical coherence alone does not guarantee statistical robustness.

Accordingly, the model must be tested to determine whether its constructs meet requirements for data suitability, internal reliability, and construct validity.

This article therefore presents the study's quantitative validation and refinement stage. A structured survey instrument was developed from the themes identified in the preceding phase and administered to stakeholders in higher education and educational technology. The analysis addresses descriptive response trends, data suitability for factor analysis, internal reliability, exploratory factor analysis, item refinement, and the development of a revised AI QMS integration model. The immediate aim is not to measure the current state of AI QMS integration in South African PHEIs. Instead, this research examines whether the proposed model can be retained or refined, and whether it is suitable for future practical application as a measurement structure (Schreiber, 2021).

2. PROBLEM STATEMENT

Despite growing interest in AI integration within South African PHEIs, empirical evidence on effective approaches to incorporating AI into academic quality management systems remains limited (Patel & Ragolane, 2024). The previous phase of this study developed a conceptual model to organise central concerns, including strategic alignment, AI literacy, ethical governance, assessment integrity, research practice, sustainability, and collaboration. Before this model can be used as a tool for institutional assessment, however, its constructs must be tested for reliability and validity (Hair et al., 2019; Schreiber, 2021).

This research therefore addresses the lack of an empirically validated AI QMS integration model in the South African PHEI context. Without such validation, the model remains conceptually useful but methodologically untested. As such this research study responds by assessing data suitability, internal reliability and construct validity, and by proposing a refined model for subsequent practical application.

3. OPERATIONALISING THE CONCEPTUAL FRAMEWORK

The conceptual model developed in the preceding article formed the basis for the quantitative phase reported here. The model emerged from conceptual exploration of artificial intelligence in higher education, a review of recent literature, and qualitative thematic analysis of stakeholder perspectives in the South African private higher education context (Bosch et al., 2025). The purpose of this section is not to repeat the qualitative findings reported in the previous article, but to explain how the model was translated into measurable constructs for statistical validation. The original model identified eight thematic areas for AI integration into Academic Quality Management Systems. These were: AI in Strategic Planning, AI Literacy and Competency Development, Ethics 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.

These eight areas were treated as the proposed constructs for the quantitative phase because they captured the main governance, academic, ethical, operational and sustainability concerns identified in the earlier phase of the study. Including AI in Strategic Planning reflects the need to embed AI adoption within institutional leadership, planning,

resource allocation, and quality assurance decision-making. This is particularly relevant in South Africa, where the Council on Higher Education's Quality Assurance Framework places responsibility on institutions to sustain internal quality systems, utilise evidence for quality decisions, and support ongoing improvement (CHE, 2022). Integration of AI into academic quality systems therefore requires not only technical adoption but also strategic alignment and institutional ownership. AI Literacy and Competency Development was included because the prior phase identified uneven levels of AI knowledge, confidence, and preparedness among stakeholders. Recent scholarship further supports this construct, arguing that AI literacy involves not only awareness of AI tools but also knowledge, capability, confidence, ethical awareness, and responsible application (Ng et al., 2024; Černý, 2024). In the context of academic quality management, AI literacy is a quality concern because staff and students cannot engage responsibly with AI if institutional capacity development is limited. Ethics and Data Privacy was included as a separate construct because AI systems raise questions about personal information, transparency, fairness, consent, accountability and data ownership. These issues are particularly relevant in South Africa because AI adoption must be considered in relation to the Protection of Personal Information Act and the wider need for responsible data governance.

Mbonye, Moodley, and Nyika (2024) demonstrate that POPIA applies to AI-driven environments, yet they also show that legal compliance alone is insufficient to address privacy risk governance, accountability, and responsible AI use. These further supports including ethics and data privacy as a core model component. AI in Teaching and Learning, and Assessment and Evaluation were treated as separate constructs in the quantitative phase. This separation is important. Although teaching, learning and assessment are closely connected in academic practice, the earlier qualitative findings suggested that AI's pedagogical value and assessment integrity concerns may not operate in the same way. While AI offers opportunities to enhance learner support, participation and the design of teaching activities, its role in assessment is more complex. It raises concerns about how student work is graded, how authorship is established, how academic integrity is protected, how assessments should be redesigned, and how much confidence institutions can place in AI-detection tools. Although AI is increasingly associated with innovation in higher education, its implications for assessment warrant closer attention. Issues such as authorship, academic misconduct, grading reliability and the uncertain accuracy of AI-detection tools point to the need for assessment-specific governance rather than broad institutional guidance alone (Nguyen et al., 2023; Dalalah & Dalalah, 2023).

AI in Research and Big Data Analytics was included to capture AI's role in literature synthesis, research support, data analysis, methodological rigour, research governance and the relationship between AI tools and human expertise. This construct was important because academic quality systems extend beyond teaching and assessment. They also include the credibility of research practices, evidence generation and responsible use of data. Including this construct allowed the model to test whether AI-enabled research practice could be treated as part of academic quality management.

The environmental impact of AI technologies was included because responsible AI integration also involves sustainability considerations. AI systems demand infrastructure, energy, and procurement decisions that may have environmental consequences. While this aspect is often marginalised in higher education AI discussions, recent African higher education research highlights that AI adoption is shaped by infrastructure, institutional preparedness, and sustainability-related constraints, especially in resource-limited contexts (Maluleke, 2025). Including this dimension allowed the model to test whether environmental responsibility could be measured as part of AI QMS integration.

Interdisciplinary Collaboration was included because AI integration into academic quality systems cannot be managed by one institutional function alone. It requires coordination between academic staff, quality assurance units, information technology, institutional leadership, governance structures and external technology partners. The qualitative phase identified collaboration as a recurring requirement for responsible implementation, while the literature on AI in education continues to emphasise the need for institutional coordination, governance and cross-functional engagement.

The survey instrument was developed from these eight proposed constructs. Each construct was measured through closed-ended statements designed to capture stakeholder perceptions of AI integration into academic quality management practice. Respondents indicated their level of agreement using a seven-point Likert scale ranging from Strongly Disagree to Strongly Agree. This scale was selected to allow sufficient variation in responses while still supporting quantitative analysis.

The operationalisation process followed both deductive and inductive logic. The constructs were drawn deductively from the conceptual model and literature, while the qualitative findings shaped the item content inductively. This approach helped to preserve continuity between the earlier model development phase and the quantitative validation phase. It also ensured that the instrument reflected the South African private higher education context rather than relying only on generic AI adoption measures.

At this point in the article, the constructs are treated as proposed constructs. They are not yet presented as validated factors. The subsequent analysis aims to determine whether these proposed constructs are suitable for exploratory factor analysis, whether their items are internally reliable, whether they form coherent factor structures, and whether the original model requires refinement. Table 1 presents the operationalisation of the proposed AI QMS integration model into measurable survey constructs.

Table 1: Mapping of conceptual themes to the survey instrument

Conceptual theme from earlier phase	Survey section and questions	Proposed quantitative construct	Code	Measurement focus
Contextual stakeholder profile	Section A, Q2 to Q5	Statistical and demographic data	N/A	Role in higher education, experience, level of responsibility and primary functional area
Overall AI QMS integration	Q6	Observed outcome variable	AI QMS INT	Overall extent to which AI is currently integrated into Academic Quality Management Systems
Strategic positioning of AI in institutional quality systems	Section B, Q7 to Q11	AI in Strategic Planning	SP	Strategic alignment, leadership vision, resource allocation, AI-informed decision making and coherent implementation planning.
AI capacity and institutional capability development	Section C, Q12 to Q18	AI Literacy and Competency Development	AL	Staff training, professional development, prompting confidence, ethical and social AI literacy, continuous learning and AI proficiency gaps
Responsible AI governance and data protection	Section D, Q19 to Q23	Ethics and Data Privacy	ED	POPIA compliance, personal data protection, transparency, fairness, consent and data ownership
AI-enabled teaching and learning practice	Section E, Q24 to Q28	AI in Teaching and Learning	TL	Personalisation, student engagement, depth and quality of student thinking, innovative learning design, responsible student use and ethical classroom integration.
AI-related assessment integrity and evaluation practice	Section F, Q29 to Q33	Assessment and Evaluation	AE	AI detection reliability, assessment policy, assessment redesign, fair and consistent grading, authorship and academic integrity guidance

AI-supported research and responsible data use	Section G, Q34 to Q39	AI in Research and Big Data Analytics	RB	Literature synthesis, verification of AI-generated outputs, data analysis rigour, ethical research policy, responsible AI data practice and human expertise
Sustainability implications of AI technologies	Section H, Q40 to Q43	Environmental Impact of AI Technologies	EI	Environmental impact, energy consumption, carbon footprint, sustainability goals, procurement, policy decisions and environmental monitoring
Cross-functional and interdisciplinary coordination	Section I, Q44 to Q48	Interdisciplinary Collaboration	IC	Collaboration between academic, IT and QA departments, cross-functional teamwork, external partnerships, collaboration barriers and AI as a social and technological innovation
Qualitative reflection on opportunity and concern	Section J, Q49 to Q50	Open-ended reflection	N/A	Greatest opportunity AI presents for academic quality, and the main concern about integrating AI into quality management processes

The mapping in Table 1 represents the starting measurement structure tested in this article. It does not assume that the original conceptual model is already empirically valid. Instead, it provides the basis for the subsequent validation process, where data suitability, reliability and factor structure are assessed. The analysis that follows determines which constructs remain stable, which require item-level refinement, and which reveal more complex subfactor behaviour.

4. OBJECTIVE OF THE STUDY

This study aims to validate and refine the proposed AI QMS integration model by quantitatively assessing data suitability, internal reliability, and construct validity. This work builds directly on the prior conceptual and qualitative phases, examining whether the previously identified thematic areas can be retained as coherent constructs. The study also seeks to determine if the model requires further refinement before it can be applied in practice within South African private higher education institutions (Hair et al., 2019; Schreiber, 2021). The objective of this phase, therefore, is to examine whether the theoretically proposed capability domains demonstrated internal coherence and whether individual items functioned appropriately within those domains.

Specifically, the article seeks to:

- Assess whether the data are suitable for exploratory factor analysis through the Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett Test of Sphericity.
- Test the internal reliability of the proposed AI QMS constructs using Cronbach's alpha coefficients.
- Evaluate the factor structure and unidimensionality of the proposed constructs to determine whether the items group coherently around the intended themes.
- Identify items that require removal, refinement, or separate conceptual consideration based on empirical results from the factor analysis.
- Develop a revised AI QMS integration model that maintains the foundational logic of the original framework while enhancing its measurement structure for future application.

The purpose is therefore not to measure the current state of AI QMS integration in South African private higher education institutions. Rather, it produces a revised measurement model that can be used in subsequent research to assess institutional positioning, identify areas for improvement and support responsible AI integration into academic quality management systems.

5. RESEARCH METHODOLOGY

This section outlines the research methodology applied to validate and refine the AI QMS integration model. The approach includes the research design, sampling strategy, data collection process, and analytical procedures, ensuring methodological rigor and alignment with best practices in recent educational research (Hair et al., 2019; Schreiber, 2021).

5.1 RESEARCH APPROACH

This article details the quantitative phase of a sequential, exploratory, mixed-methods study. The focus here is to test the reliability and empirical coherence of the AI QMS integration model, which was previously developed using conceptual and qualitative techniques. This phase examines whether the proposed constructs function as robust measurement areas when evaluated with empirical data. The broader mixed-methods design integrates the interpretive depth gained from the qualitative phase with a quantitative assessment of the model's structure. This approach aligns with best practice in exploratory sequential designs, where qualitative findings guide the development and validation of quantitative instruments (Dawadi et al., 2021; Creswell & Plano Clark, 2018). This phase is informed by a pragmatist paradigm with positivist features. Pragmatism suits the study because it synthesises multiple forms of evidence to address both practical and conceptual questions about integrating artificial intelligence into Academic Quality Management Systems within South African private higher education. The positivist aspect is reflected in the use of statistical procedures to assess data suitability, internal reliability, and construct validity. Thus, the current article focuses on validating and refining the proposed model before implementation, rather than repeating the qualitative analysis or measuring the current state of AI QMS integration.

5.1.1 Research Design

The quantitative phase used a cross-sectional survey design, which was appropriate for capturing stakeholder perceptions at a specific point in time and testing the coherence of the proposed survey constructs. Cross-sectional designs are widely used to investigate perceptions, attitudes, or reported practices within a defined group, with the understanding that they do not establish causality or changes over time (Wang & Cheng, 2020).

We collected quantitative data using an online questionnaire administered via SurveyMonkey. The questionnaire was developed from the conceptual model and prior qualitative insights. It included demographic items, one global question assessing the perceived extent of AI integration into Academic Quality Management Systems, eight construct-specific sections, and two open-ended prompts for reflection. The structure allowed for comprehensive measurement of both respondent context and perceptions of AI QMS integration. The survey comprised 40 questions that measured eight constructs: AI in Strategic Planning, AI Literacy and Competency Development, Ethics 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. Responses were captured on a seven-point Likert scale ranging from Strongly Disagree to Strongly Agree, consistent with established survey research practices (Jebb, Ng & Tay, 2021; Ferrando et al., 2025). The scale supported detailed analysis of attitudes and perceptions.

5.2 DATA COLLECTION

For the quantitative component of the study, participants provided responses through an electronically distributed questionnaire hosted on SurveyMonkey. The survey operationalised and tested the thematic constructs that emerged from the preceding conceptual and qualitative phase. The instrument included contextual respondent information, one global item measuring the perceived extent of AI integration into Academic Quality Management Systems, eight proposed construct sections, and two open-ended reflection questions.

The eight measured constructs were: (1) AI in Strategic Planning, (2) AI Literacy and Competency Development, (3) Ethics and Data Privacy, (4) AI in Teaching and Learning, (5) Assessment and Evaluation, (6) AI in Research and Big Data Analytics, (7) Environmental Impact of AI Technologies, and (8) Interdisciplinary Collaboration.

Each construct section featured closed-ended statements designed as measurable items, drawing from qualitative findings and aligned with current literature on AI in higher education, ethical governance, AI literacy, assessment integrity, and academic quality management (Černý, 2024; Nguyen et al., 2023). The seven-point Likert response format enabled nuanced differentiation in agreement, facilitating both descriptive and psychometric analysis.

The team distributed a call for participation through professional and public digital channels, including LinkedIn, Facebook, higher education networks, private PHEI contacts, and EdTech forums. The survey introduction explained the purpose, ethical considerations, and informed consent process. Participation was voluntary and anonymous, and the study collected no identifying information. Data management adhered to the 2013 Protection of Personal Information Act (POPIA) (SA, 2013). Only participants who provided informed consent could continue to the questionnaire. This ensured ethical participation and data protection, while allowing for a diverse range of stakeholder input relevant to AI integration in South African private higher education.

5.2.1 Target Population

The target population comprised stakeholders with knowledge of, or professional involvement in, Artificial Intelligence, academic quality management, higher education governance, teaching and learning, assessment, research, information technology, quality assurance or education technology within the South African private higher education context.

This included academic staff, institutional leaders, quality assurance practitioners, IT professionals, professional and operational staff, and external industry specialists. The inclusion of multiple stakeholder groups was necessary because AI QMS integration is not confined to a single institutional function. It involves academic, governance, technical, quality-assurance, research, and operational dimensions. A diverse respondent group, therefore, allowed the study to test whether the constructs developed in the preceding phase could be assessed across the stakeholder groups most likely to engage with AI-related academic quality work.

5.2.2 Sampling

A non-probability purposive sampling strategy was employed to recruit participants with relevant experience in higher education, quality assurance, AI integration, governance, or educational technology. This approach suited the study's aim of validating and refining the AI QMS measurement model, rather than estimating prevalence across the sector. Purposive sampling is widely endorsed for research where participants are selected for their contextual expertise (Etikan, Musa & Alkassim, 2016). The survey was distributed through targeted and open digital channels, including LinkedIn, professional higher education networks, private higher education contacts, EdTech forums and sector-related networks accessed through the researcher's professional networks. Since the invitation was shared through open, network-based channels, the total number of eligible individuals who viewed it could not be determined. A formal response rate was consequently not calculated. We recorded 85 survey cases. After consent screening, 82 cases were eligible for inclusion.

The usable sample differed across analyses due to missing data. The validation procedures reported were based on the available responses for each statistical procedure, as shown in Table 2.

Table 2: Usable sample by statistical procedure

Statistical procedure	Purpose of the article	Usable sample
Frequency distributions	Descriptive response patterns across proposed AI QMS constructs	72
KMO and Bartlett tests	Suitability of data for factor analysis	72
Exploratory factor analysis	Construct structure and item refinement	72
Cronbach alpha	Internal reliability of retained constructs	72

Correlation and regression analysis	Supporting relationship testing where applicable	60
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The sample size was considered acceptable for exploratory validation, with appropriate caution. A construct-to-construct exploratory factor analysis (EFA) was conducted at the construct level, with each construct containing a limited set of items. The intention of this study, however, was not to discover an entirely new latent structure from an atheoretical item pool. The instrument was derived from a previously established conceptual framework produced through extensive literature review and qualitative analysis. The study, therefore, examined whether the theoretical antecedents are unidimensional in nature and measured by their respective criteria. For this reason, exploratory factor analyses were conducted at construct level to refine proposed dimensions rather than to search for an unrestricted alternative factor structure.

Recent methodological literature cautions against rigid sample size rules in EFA, as adequacy depends on the model, item behaviour, and clarity of factor solutions (Schreiber, 2021; Ferrando & Lorenzo-Seva, 2018). All constructs met the suitability requirements for factor analysis, with Kaiser-Meyer-Olkin values above 0.60 and significant Bartlett's Test of Sphericity results. The sample supports model refinement within this stakeholder group but is not generalisable to all South African PHEIs.

5.3 Description of Analysis

Quantitative data analysis was conducted using SPSS, following a structured process that included data screening, descriptive statistics, assessment of suitability for factor analysis, reliability checks, examination of the factor structure, and item refinement. The analysis aimed to validate and improve the measurement structure developed in earlier conceptual and qualitative phases, in line with recent best practices (Cortina, 1993; Schreiber, 2021). Initial data screening confirmed consent, excluded incomplete responses, and assessed missing data across survey items. Analyses reported usable sample sizes, which varied across descriptive, factor-analytic, and supplementary analyses. Descriptive analyses calculated frequencies and percentages to summarise response patterns across the eight AI QMS constructs. For interpretive clarity, Likert scale responses were grouped into Disagree, Neutral, and Agree categories. This grouping clarified response patterns and was not used for construct validation or item retention decisions. Before exploratory factor analysis, we calculated the Kaiser-Meyer-Olkin measure of sampling adequacy and the Bartlett Test of Sphericity for each construct to assess suitability for factor extraction. EFA was conducted at the construct level, using eigenvalues and scree plots to guide factor retention, and item loadings to assess alignment with intended constructs. This approach is consistent with current recommendations for validating measurement models in educational research (Schreiber, 2021). Current methodological literature also cautions against applying fixed sample size rules mechanically, as adequacy depends on the specified model, item behaviour, factor loadings and clarity of the factor solution (Ferrando & Lorenzo-Seva, 2018). Cronbach's alpha, a widely accepted measure in educational and behavioural research assessed the reliability and internal consistency was assessed using . Reliability results were interpreted alongside factor structure, item loadings, and conceptual fit, as Cronbach's alpha alone does not establish validity (Cortina, 1993; Schreiber, 2021). We based decisions about item retention or removal on a combined interpretation of factor structure, loadings, reliability, and conceptual fit. Items were eliminated if they failed to align with the intended factor, loaded separately, or reduced empirical coherence. Removal decisions were based on statistical behaviour within the measurement structure, not on respondent agreement levels. Pearson correlations and multiple regression were used as supplementary analyses where appropriate. However, the primary aim was construct validation and refinement, so regression results were interpreted cautiously and primarily supported the refined model structure. Future research will apply the model to measure the current state of AI QMS integration. This systematic, staged analytical approach enabled a rigorous assessment of the AI QMS integration model. Descriptive statistics, KMO and Bartlett tests, EFA, reliability analysis, and item refinement collectively transformed the model from a conceptual framework to an evidence-based measurement structure.

6. RESULTS

6.1 Descriptive overview of response patterns

Descriptive frequency distributions were calculated to provide an initial overview of stakeholder perceptions across the proposed AI QMS constructs. Responses were collected on a seven-point Likert scale and grouped into three reporting categories: Disagree, Neutral and Agree. This descriptive analysis sets the context for the validation process. These groupings were not used to assess construct validity or to retain survey items. The descriptive results indicate that respondents generally recognised the strategic and academic relevance of AI in quality management. Within AI in Strategic Planning, most respondents agreed that AI initiatives are aligned with institutional strategic goals (69.44%), that institutional leadership communicates a clear vision for AI integration (71.83%), and that institutional decision-making processes actively consider AI implications (72.22%). However, the same construct also showed weaker agreement regarding implementation capacity. Only 47.22% agreed that adequate financial and human resources are allocated to AI-related activities, while 55.56% agreed that their institution has a coherent plan guiding AI implementation. This suggests that strategic intent is more visible than the resourcing and planning capacity required to support implementation.

AI Literacy and Competency Development showed a similarly mixed pattern. Respondents reported relatively strong agreement that institutions promote continuous learning to keep pace with AI developments (70.83%) and that AI literacy training includes ethical and social dimensions of AI use (67.14%). However, only 47.22% agreed that staff receive adequate training to use AI tools effectively. At the same time, 68.06% agreed that AI proficiency differs noticeably between students and staff, and 59.72% agreed that differences in AI skills between departments hinder collaboration. These results point to recognised capability gaps, particularly in formal staff training and consistency of AI competence across institutional groups.

The Ethics and Data Privacy construct showed the strongest agreement for formal policy compliance. A total of 85.92% of respondents agreed that their institution has clear policies to ensure compliance with the Protection of Personal Information Act.

Agreement dropped into the more moderate range when respondents were asked about the practical side of data governance: staff understanding of personal data protection when using AI tools (60.56%), transparency in how AI systems manage and store data (61.11%), trust in the fairness and transparency of institutional AI tools (58.33%), and clarity around consent and data ownership (56.34%). In effect, respondents appeared more certain that formal POPIA-related policies exist than they were about how confidently those principles are understood, communicated and applied in everyday AI use.

The AI in Teaching and Learning results show strong support for AI's pedagogical value. The highest agreement was recorded for AI assisting educators in designing more innovative learning experiences (83.10%). Respondents also agreed that AI tools enhance personalisation and student engagement (70.42%), that educators understand how to integrate AI ethically into classroom practice (71.43%), and that AI tools influence the depth and quality of student thinking (64.79%). The weakest item concerned responsible student use, with only 50.70% agreement that students use AI responsibly under current institutional guidelines, suggesting respondents were more confident in AI's teaching and learning value than in the governance of student use.

Assessment and Evaluation produced one of the more uneven descriptive patterns. Respondents showed relatively strong agreement that assessment policies have been updated to address AI use (77.14%) and that AI can support fair and consistent grading when used appropriately (78.26%). However, only 32.86% agreed that AI detection tools provide dependable results, while 55.71% disagreed. Educator confidence in redesigning assessments for the AI era was also more moderate, with 52.17% agreement. It can be derived that assessment policy and grading support are viewed more positively than AI detection reliability and assessment redesign readiness.

AI in Research and Big Data Analytics showed some of the strongest agreement levels in the descriptive data. Respondents agreed that AI complements rather than replaces human expertise in research (85.29%) and that AI-generated research outputs are verified before use (85.29%). Agreement was also high that AI tools help researchers synthesise literature efficiently (80.60%), that AI enhances data analysis without compromising methodological rigour (72.06%), and that institutional policies guide the ethical use of AI in research (70.59%). The weaker area was training,

with only 46.27% agreeing that researchers receive training in responsible AI data analysis practices, saying that AI is valued in research activity, but training for responsible research use remains less developed.

The environmental impact of AI Technologies showed the weakest descriptive pattern across the constructs. Less than half of respondents agreed that their institution considers the environmental impact of AI technologies (47.06%). Agreement was lower for awareness of AI's energy consumption and carbon footprint (35.29%), for the integration of sustainability goals into AI procurement and policy decisions (30.88%), and for the use of environmental monitoring data to guide AI implementation decisions (23.53%). This indicates that environmental sustainability is not yet strongly visible in AI-related quality management practice.

Interdisciplinary Collaboration showed that respondents recognised the importance of collaboration but also identified coordination gaps. A total of 74.63% agreed that staff view AI as both a technological and a social innovation that requires collaboration. Agreement was also recorded for institutional culture supporting cross-functional teamwork on AI projects (64.71%) and for collaboration between academic, IT and QA departments (61.76%). External partnerships showed weaker agreement (47.06%), while 72.06% of respondents agreed that limited cross-department collaboration slows AI integration, suggesting that collaboration is recognised as important but is not yet consistently supported through internal coordination or external institutional partnerships.

Overall, the descriptive results show a clear distinction between recognition of AI's strategic, academic and research value, and confidence in the systems needed to support responsible implementation. Stronger agreement was evident regarding strategic alignment, leadership vision, innovative learning design, POPIA-related policy compliance, research verification, and human expertise. Weaker agreement was evident in relation to resourcing, staff training, responsible AI research training, dependable AI detection tools, external partnerships and environmental sustainability. These patterns provide useful context, but the model's validation depends on the suitability and reliability, as well as the exploratory factor analysis results that follow.

Table 3: Descriptive Results of Response Patterns

Construct	Item	Statement	Disagree %	Neutral %	Agree %
AI in Strategic Planning	SP1	AI initiatives are clearly aligned with my institution's strategic goals.	16.67	13.89	69.44
AI in Strategic Planning	SP2	Institutional leadership communicates a clear vision for AI integration.	19.72	8.45	71.83
AI in Strategic Planning	SP3	Adequate financial and human resources are allocated to AI-related activities.	36.11	16.67	47.22
AI in Strategic Planning	SP4	Institutional decision-making processes actively consider AI implications.	16.67	11.11	72.22
AI in Strategic Planning	SP5	My institution has a coherent plan guiding AI implementation.	30.56	13.89	55.56
AI Literacy and Competency Development	AL1	Staff receive adequate training to use AI tools effectively.	41.67	11.11	47.22
AI Literacy and Competency Development	AL2	There are noticeable differences in AI proficiency between students and staff.	9.72	22.22	68.06

AI Literacy and Competency Development	AL3	Professional development programmes include AI-related competencies.	25.00	16.67	58.33
AI Literacy and Competency Development	AL4	Staff feel confident in prompting and refining AI outputs.	16.90	25.35	57.75
AI Literacy and Competency Development	AL5	AI literacy training includes ethical and social dimensions of AI use.	17.14	15.71	67.14
AI Literacy and Competency Development	AL6	My institution promotes continuous learning to keep pace with AI developments.	15.28	13.89	70.83
AI Literacy and Competency Development	AL7	Differences in AI skills between departments hinder collaboration.	18.06	22.22	59.72
Ethics and Data Privacy	ED1	My institution has clear policies to ensure compliance with the Protection of Personal Information Act.	11.27	2.82	85.92
Ethics and Data Privacy	ED2	Staff understand how to protect personal data when using AI tools.	28.17	11.27	60.56
Ethics and Data Privacy	ED3	The institution is transparent about how AI systems manage and store data.	25.00	13.89	61.11
Ethics and Data Privacy	ED4	I trust that AI tools used institutionally are transparent and fair.	18.06	23.61	58.33
Ethics and Data Privacy	ED5	There is clarity about consent and data ownership when AI is used in teaching or research.	22.54	21.13	56.34
AI in Teaching and Learning	TL1	AI tools enhance personalisation and student engagement in learning.	12.68	16.90	70.42
AI in Teaching and Learning	TL2	AI tools influence the depth and quality of student thinking.	21.13	14.08	64.79
AI in Teaching and Learning	TL3	AI assists educators in designing more innovative learning experiences.	5.63	11.27	83.10
AI in Teaching and Learning	TL4	Students use AI responsibly under current institutional guidelines.	33.80	15.49	50.70
AI in Teaching and Learning	TL5	Educators understand how to integrate AI ethically into classroom practice.	17.14	11.43	71.43
Assessment and Evaluation	AE1	AI detection tools provide dependable results.	55.71	11.43	32.86

Assessment and Evaluation	AE2	Assessment policies have been updated to address AI use.	12.86	10.00	77.14
Assessment and Evaluation	AE3	Educators are confident in redesigning assessments for the AI era.	26.09	21.74	52.17
Assessment and Evaluation	AE4	AI can support fair and consistent grading when used appropriately.	10.14	11.59	78.26
Assessment and Evaluation	AE5	The institution provides guidance on authorship and academic integrity in the context of AI.	18.57	21.43	60.00
AI in Research and Big Data Analytics	RB1	AI tools assist researchers in synthesising literature efficiently.	7.46	11.94	80.60
AI in Research and Big Data Analytics	RB2	I verify all AI-generated research outputs before using them.	5.88	8.82	85.29
AI in Research and Big Data Analytics	RB3	AI enhances data analysis without compromising methodological rigour.	11.76	16.18	72.06
AI in Research and Big Data Analytics	RB4	Institutional policies guide ethical use of AI in research.	13.24	16.18	70.59
AI in Research and Big Data Analytics	RB5	Researchers receive training in responsible AI data analysis practices.	35.82	17.91	46.27
AI in Research and Big Data Analytics	RB6	AI is viewed as complementing, not replacing, human expertise in research.	4.41	10.29	85.29
Environmental Impact of AI Technologies	EI1	My institution considers the environmental impact of AI technologies.	35.29	17.65	47.06
Environmental Impact of AI Technologies	EI2	There is awareness of AI's energy consumption and carbon footprint.	47.06	17.65	35.29
Environmental Impact of AI Technologies	EI3	Sustainability goals are integrated into AI procurement and policy decisions.	42.65	26.47	30.88
Environmental Impact of AI Technologies	EI4	Environmental monitoring data are used to guide AI implementation decisions.	54.41	22.06	23.53
Interdisciplinary Collaboration	IC1	AI initiatives involve collaboration between academic, IT, and QA departments.	26.47	11.76	61.76

Interdisciplinary Collaboration	IC2	Institutional culture supports cross-functional teamwork on AI projects.	22.06	13.24	64.71
Interdisciplinary Collaboration	IC3	External partnerships support AI implementation.	22.06	30.88	47.06
Interdisciplinary Collaboration	IC4	Limited collaboration across departments slows progress on AI integration.	10.29	17.65	72.06
Interdisciplinary Collaboration	IC5	Staff view AI as both a technological and social innovation requiring collaboration.	5.97	19.40	74.63

6.2 Suitability of the data

The data was checked to identify any out-of-range data entries that do not comply with the seven-point Likert scale. In addition, the distribution of the data was also investigated by calculating the skewness and kurtosis to determine how well it fits the normal Bell-curve distribution (see Table 4) (Pallant, 2020).

Table 4: Descriptive statistics and Normality Assessment of Variables

Variable	Mean	Minimum	Maximum	Std.Dev.	Skewness	Kurtosis
SPTot	4,600	1,000	7,000	1,396	-0,764	0,224
ALTot	4,539	1,000	6,600	1,242	-0,673	0,118
EDTot	4,910	1,000	7,000	1,478	-0,770	0,230
TLTot	5,258	1,000	7,000	1,281	-0,756	0,699
AETot	4,974	1,000	7,000	1,070	-0,806	1,908
RBTot	5,000	2,000	7,000	1,176	-0,200	-0,578
EITot	3,801	1,000	7,000	1,434	0,056	-0,578
ICTot	4,735	2,000	7,000	1,122	-0,325	-0,019

The descriptive statistics show generally moderate-to-high response patterns across most constructs, with mean scores ranging from 3.801 for EITot to 5.258 for TLTot on a seven-point scale. Most constructs were above the scale midpoint of 4, while EITot fell slightly below it. TLTot, AETot and RBTot recorded comparatively higher mean values, reflecting stronger respondent agreement in these areas. EITot was lower than the other constructs, pointing to weaker attention to environmental impact considerations. The standard deviations, ranging from 1.070 to 1.478, show moderate spread in the responses and enough variation for further analysis (Hair et al., 2019).

Assessment of distributional properties further supports the suitability of the data for parametric analysis. Skewness values fall within an acceptable range (-0.806 to 0.056), although most variables exhibit slight negative skewness (Field, 2017).

This indicates that responses are somewhat clustered toward the higher end of the scale. Kurtosis values, ranging from -0.578 to 1.908, also remain within acceptable thresholds, suggesting no substantial departure from normality (Field, 2017). Although AETot displays a moderately leptokurtic distribution, the overall pattern across variables indicates approximately normal distributions. Collectively, these results suggest that the dataset did not show severe departures from normality, supporting the use of parametric statistical techniques in subsequent analyses (Hair et al., 2019; Field, 2017). In practice, this means that the data can be analysed using multivariate statistical techniques.

Before conducting exploratory factor analysis, the suitability of the data was assessed using the Kaiser-Meyer-Olkin measure of sampling adequacy and the Bartlett Test of Sphericity. These tests were conducted separately for each proposed construct, as the purpose of the analysis was to determine whether the items within each construct were sufficiently related to proceed with factor analysis.

The Kaiser-Meyer-Olkin values ranged from 0.65 to 0.88, with all constructs exceeding the minimum acceptable threshold of 0.60 (Field, 2017). The lowest value (0.65) appeared in AI in Teaching and Learning, and the highest in Ethics and Data Privacy, which still indicates an acceptable sample. This means that the sample is adequate and that sufficient data entries are available to analyse the data further. Bartlett's Test of Sphericity was significant for all constructs ($p < 0.05$), confirming that the correlation matrices were suitable for factor analysis. Taken together, these results indicate that all proposed constructs were appropriate for exploratory factor analysis.

Table 5: KMO and Bartlett Test of Sphericity by construct

Construct	Items	KMO	Bartlett chi-square	df	p value	Interpretation
AI in Strategic Planning	5	0.84	183.37	10	< 0.05	Suitable for factor analysis
AI Literacy and Competency Development	7	0.81	165.52	21	< 0.05	Suitable for factor analysis
Ethical Considerations and Data Privacy	5	0.88	291.15	10	< 0.05	Suitable for factor analysis
AI Driven Teaching and Learning Methods	5	0.65	148.54	10	< 0.05	Suitable for factor analysis
AI in Assessment and Evaluation	5	0.73	81.34	10	< 0.05	Suitable for factor analysis
AI in Research and Big Data Analytics	6	0.70	124.31	15	< 0.05	Suitable for factor analysis
Environmental Impact of AI Technologies	4	0.74	248.54	6	< 0.05	Suitable for factor analysis
Interdisciplinary Collaboration	5	0.73	84.45	10	< 0.05	Suitable for factor analysis

The findings confirm that the data met the fundamental requirements for factor analysis. This allowed the analysis to proceed to examining the factor structure for each proposed construct.

6.3 Reliability of the proposed constructs

Cronbach's alpha coefficients were calculated to assess the internal consistency of the proposed constructs. All constructs recorded alpha values above 0.70, indicating acceptable to excellent reliability (Nunnally & Bernstein, 1994; Cortina, 1993; Field, 2017). Ethics and Data Privacy recorded the highest alpha coefficient at 0.93, followed by Environmental Impact of AI Technologies at 0.92 and AI in Strategic Planning at 0.88. AI Literacy and Competency Development recorded an alpha value of 0.85, while AI in Teaching and Learning recorded 0.83. Assessment and Evaluation recorded 0.75, while AI in Research and Big Data Analytics and Interdisciplinary Collaboration both recorded 0.77.

Table 6: Cronbach alpha coefficients for the proposed constructs

Construct	Cronbach alpha	Interpretation
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AI in Strategic Planning	0.88	Excellent
AI Literacy and Competency Development	0.85	Excellent
Ethical Considerations and Data Privacy	0.93	Excellent
AI Driven Teaching and Learning Methods	0.83	Excellent
AI in Assessment and Evaluation	0.75	Good
AI in Research and Big Data Analytics	0.77	Good
Environmental Impact of AI Technologies	0.92	Excellent
Interdisciplinary Collaboration	0.77	Good

These results suggest that the proposed constructs demonstrated acceptable internal consistency. However, reliability alone is not enough to confirm construct validity. Cronbach's coefficient alpha indicates whether items behave consistently as a group, but it does not confirm the underlying factor structure. For this reason, reliability results were analysed together with the exploratory factor analysis results described in the following sections.

6.4 Exploratory factor analysis and construct refinement

A construct-to-construct exploratory factor analysis was conducted separately for each proposed construct to determine whether the items grouped into coherent factor structures. We guided the number of factors retained by eigenvalues greater than one and inspection of the scree plots. We applied a factor-loading threshold of 0.65 ($p \leq 0.05$) for item retention, based on the sample size of 72 respondents (Hair et al., 2019). Where the initial EFA indicated split factors, weak loadings or item misalignment, the relevant items were reviewed, and the analysis was rerun using the retained item set. Where an item loaded marginally below the threshold, it was considered for cautious retention if it remained conceptually central to the construct, did not distort the factor interpretation, and contributed meaningfully to the model's theoretical structure. Only factors with eigenvalues of one or higher were considered.

6.4.1 AI in Strategic Planning

Table 7: EFA loadings for AI in Strategic Planning, n = 72

Item	Factor 1
SP3	0.857
SP5	0.856
SP2	0.844
SP4	0.802
SP1	0.750
Total variance explained: 67.7%	
Eigenvalue for Factor 1: 3.384	

AI in Strategic Planning produced a clear one-factor solution. All five items loaded above the 0.65 threshold, with loadings ranging from 0.750 to 0.857. The factor explained 67.7% of the variance. No items were removed from the construct, indicating that statements about strategic alignment, leadership vision, resource allocation, AI-informed decision-making, and coherent implementation planning all functioned together as a single strategic planning factor.

6.4.2 AI Literacy and Competency Development

The initial EFA for AI Literacy and Competency Development produced a two-factor structure. AL5, AL6, AL1, AL4 and AL3 loaded on the first factor, while AL7 and AL2 loaded on the second factor. The split shows that

the original item set combined two related but distinct issues: *Institutional AI literacy development* and *Uneven AI proficiency across students, staff or departments*.

Table 8: Initial EFA loadings for AI Literacy and Competency Development, n = 72

Item	Factor 1	Factor 2
AL5	0.839	0.141
AL6	0.821	0.165
AL1	0.788	-0.022
AL4	0.786	-0.071
AL3	0.679	0.395
AL7	-0.006	0.852
AL2	0.231	0.661
Total variance explained: 64.3%		

In Sub-factor 1 (*Institutional AI literacy development*), the loadings ranged from 0.744 to 0.857, and the factor explained 63.1% of the variance. The refined construct is best understood as institutional AI literacy development, with emphasis on training, professional development, prompting confidence, ethical and social AI literacy, and continuous learning.

Sub-factor 2 (*Uneven AI proficiency across students, staff, or departments*) comprises two high-loading items addressing uneven proficiency in AI. AI proficiency ranges from students, staff, and even higher education departments that have not used AI at all, to expert-level users. AL2 and AL7 were therefore separated from the retained factor structure, and the EFA was rerun using AL1, AL3, AL4, AL5 and AL6.

Table 9: Refined EFA loadings for AI Literacy and Competency Development, n = 72

Item	Factor 1
AL5	0.857
AL6	0.845
AL4	0.762
AL1	0.756
AL3	0.744
Total variance explained: 63.1%	
Eigenvalue for Factor 1: 3.156	

After refinement, the construct produced a clear one-factor solution. The retained items had loadings between 0.744 and 0.857, and the factor explained 63.1% of the variance. The refined construct can be interpreted as representing institutional AI literacy development, with an emphasis on training, professional development, confidence, ethical and social AI literacy, and continuous learning.

6.4.3 Ethical Considerations and Data Privacy

Table 10: EFA loadings for Ethics and Data Privacy, n = 72

Item	Factor 1
ED1	0.817
ED2	0.914

ED3	0.863
ED4	0.921
ED5	0.913
Total variance explained: 78.6%	
Eigenvalue for Factor 1: 3.929	

Ethics and Data Privacy produced a strong one-factor solution. All five items exceeded the 0.65 threshold, with loadings ranging from 0.817 to 0.921, and the factor explained 78.6% of the variance. No items were removed. POPIA compliance, personal data protection, transparency, fairness, consent and data ownership therefore operated together as a coherent ethics and data governance factor.

6.4.4 AI in Teaching and Learning

The initial EFA for AI in Teaching and Learning produced a two-factor structure. TL1, TL2 and TL3 loaded on the first factor, while TL4 and TL5 loaded strongly on the second. The split separates AI's pedagogical contribution from questions of responsible student use and ethical classroom integration.

Table 11: Initial EFA loadings for AI in Teaching and Learning, n = 72

Item	Factor 1	Factor 2
TL1	0.893	0.119
TL2	0.809	0.184
TL3	0.879	0.127
TL4	0.115	0.919
TL5	0.149	0.905
Total variance explained: 79.8%		

TL4 and TL5 were removed from the main teaching and learning factor because they focused on responsible student use and ethical classroom integration, rather than the pedagogical contribution of AI. The EFA was then rerun with TL1, TL2, and TL3.

Table 12: Refined EFA loadings for AI in Teaching and Learning, n = 72

Item	Factor 1
TL1	0.901
TL3	0.885
TL2	0.833
Total variance explained: 76.3%	
Eigenvalue for Factor 1: 2.288	

TL4 and TL5 were removed from the main teaching and learning factor, and the EFA was rerun using TL1, TL2 and TL3. The refined factor produced strong loadings between 0.833 and 0.901 and explained 76.3% of the variance. The revised construct captures the pedagogical role of AI in personalisation, student engagement, student thinking and innovative learning design.

TL4 and TL5 remain conceptually relevant, but they were not part of the core teaching and learning factors in this sample.

6.4.5 Assessment and Evaluation

The initial EFA for Assessment and Evaluation produced one factor. However, AE1 loaded below the 0.65 retention threshold. This item focused on the dependability of AI detection tools, which did not align closely with the other assessment and evaluation items.

Table 13: Initial EFA loadings for Assessment and Evaluation, n = 72

Item	Factor 1
AE3	0.819
AE2	0.814
AE5	0.680
AE4	0.651
AE1	0.475
Total variance explained: 48.9%	
Eigenvalue for Factor 1: 2.445	

AE1 was removed because it did not meet the retention threshold. The EFA was then rerun using AE2, AE3, AE4, and AE5.

Table 14: Refined EFA loadings for Assessment and Evaluation, n = 72

Item	Factor 1
AE2	0.820
AE3	0.818
AE5	0.718
AE4	0.665
Total variance explained: 57.5%	
Eigenvalue for Factor 1: 2.299	

After removing AE1, the retained items loaded between 0.665 and 0.820, with the factor explaining 57.5% of the variance. The refined construct now represents assessment policy, assessment redesign, fair and consistent grading, and guidance on authorship and academic integrity. Removing AE1 separates confidence in AI detection tools from the broader assessment and evaluation factor, which is more closely concerned with assessment policy, redesign, grading fairness, and guidance on authorship and academic integrity.

6.4.6 AI in Research and Big Data Analytics

AI in Research and Big Data Analytics produced the most complex EFA result. The initial analysis produced a two-factor structure. RB4 and RB5 loaded strongly on the first factor, while RB1 and RB2 loaded on the second. RB3 and RB6 showed less stable behaviour in the initial solution, with RB6 showing some association with both factors. This pattern indicated that the original construct combined research activity, research governance, and human oversight into a single broad set of items.

Table 15: Initial EFA loadings for AI in Research and Big Data Analytics, n = 72

Item	Factor 1	Factor 2
RB5	0.897	0.028
RB4	0.880	0.077
RB6	0.622	0.517

RB3	0.357	0.569
RB1	0.067	0.853
RB2	0.031	0.817
Total variance explained: 68.2%		

RB1 and RB2 reflected AI-supported research activity, while RB4 and RB5 focused on institutional research governance and responsible AI practice. RB3 and RB6 did not fit cleanly into either group in the initial solution. A follow-up analysis confirmed this separation, with RB1 and RB2 loading together and RB4 and RB5 loading as a separate factor.

RB3 did not contribute cleanly to the retained structure. RB6 was reconsidered because, conceptually, the complementary role of human expertise aligns more closely with responsible research governance than with technical research support activity. The EFA was, as a result, rerun using RB4, RB5 and RB6.

Table 16: Follow-up EFA loadings for AI in Research and Big Data Analytics, n = 72

Item	Factor 1	Factor 2
RB1	0.086	0.871
RB2	0.073	0.878
RB4	0.908	0.109
RB5	0.917	0.044
Total variance explained: 80.5%		

The refined three-item factor explained 68.8% of the variance, with loadings ranging from 0.740 to 0.875. The retained RB factor is narrower than the original construct and is best interpreted as *Research governance and responsible AI use*. RB1, RB2 and RB3 should not be treated as conceptually irrelevant. Rather, they appear to represent *AI-supported research practice*, which may warrant development as a separate subdimension in future work.

Table 17: Refined EFA loadings for AI in Research and Big Data Analytics, n = 72

Item	Factor 1
RB4	0.875
RB5	0.866
RB6	0.740
Total variance explained: 68.8%	
Eigenvalue for Factor 1: 2.065	

6.4.7 Environmental Impact of AI Technologies

Table 18: EFA loadings for Environmental Impact of AI Technologies, n = 72

Item	Factor 1
EI4	0.928
EI3	0.917
EI2	0.881
EI1	0.881
Total variance explained: 81.3%	

Eigenvalue for Factor 1: 3.254

The Environmental Impact of AI Technologies produced a clear one-factor solution. All four items exceeded the 0.65 threshold, with loadings ranging from 0.881 to 0.928. The factor explained 81.3% of the variance. No items were removed, indicating that environmental impact, energy awareness, sustainability integration and environmental monitoring operated together as a coherent factor.

6.4.8 Interdisciplinary Collaboration

The initial EFA for Interdisciplinary Collaboration produced a two-factor structure. IC1, IC2, IC3 and IC5 loaded on the first factor, while IC4 loaded strongly on the second factor. IC4 was framed as a barrier statement, measuring the effect of limited collaboration rather than collaboration capability itself. We therefore removed it before rerunning the EFA.

Table 19: Initial EFA loadings for Interdisciplinary Collaboration, n = 72

Item	Factor 1	Factor 2
IC2	0.878	0.079
IC1	0.800	0.043
IC3	0.790	0.063
IC5	0.605	-0.198
IC4	0.047	0.981
Total variance explained: 68.3%		

IC4 was removed because it did not load with the main collaboration factor. The EFA was then rerun using IC1, IC2, IC3 and IC5.

Table 20: Refined EFA loadings for Interdisciplinary Collaboration, n = 72

Item	Factor 1
IC2	0.880
IC1	0.802
IC3	0.792
IC5	0.596
Total variance explained: 60.0%	
Eigenvalue for Factor 1: 2.401	

The refined factor explained 60.0% of the variance. IC1, IC2 and IC3 loaded strongly, while IC5 loaded below the preferred 0.65 threshold at 0.596. IC5 was retained with caution because it remained conceptually aligned with the construct and captured the broader understanding of AI as both a technological and social innovation. Removing IC5 would have narrowed the construct to operational collaboration only, while retaining it preserved the broader socio-technical meaning of interdisciplinary collaboration identified in the earlier qualitative phase.

The refined factor focuses on collaboration among academic, IT, and quality assurance roles, cross-functional teamwork, external partnerships, and the social dimension of AI integration.

6.5 Refined AI QMS Factor Structure

The exploratory factor analysis supported the proposed AI QMS integration model, but the original form was not retained in its entirety. Three constructs were retained without modification: AI in Strategic Planning, Ethics and

Data Privacy, and Environmental Impact of AI Technologies. Each of these produced clear one-factor structures with strong item loadings.

Other constructs required refinement. For example, AI Literacy and Competency Development was narrowed to focus on institutional training and development, with items related to proficiency gaps separated from the final retained factor. AI in Teaching and Learning was adjusted to focus primarily on pedagogical aspects, while items related to responsible use were separated. Assessment and Evaluation omitted the item concerning the dependability of AI detection tools. AI in Research and Big Data Analytics was refined to highlight governance and responsible use, while AI-supported research practice was separated from the final retained factor. Interdisciplinary Collaboration was similarly adjusted to better represent collaborative capability.

Table 21: Refined factor structure of the AI QMS integration model

Construct	Final status	Retained items	Items removed or separated from final factor
AI in Strategic Planning	Retained unchanged	SP1, SP2, SP3, SP4, SP5	None
AI Literacy and Competency Development	Refined	AL1, AL3, AL4, AL5, AL6	AL2, AL7
Ethical Considerations and Data Privacy	Retained unchanged	ED1, ED2, ED3, ED4, ED5	None
AI Driven Teaching and Learning Methods	Refined	TL1, TL2, TL3	TL4, TL5
AI in Assessment and Evaluation	Refined	AE2, AE3, AE4, AE5	AE1
AI in Research and Big Data Analytics	Refined and narrowed	RB4, RB5, RB6	RB1, RB2, RB3
Environmental Impact of AI Technologies	Retained unchanged	EI1, EI2, EI3, EI4	None
Interdisciplinary Collaboration	Refined	IC1, IC2, IC3, IC5	IC4

The removal or separation of items does not suggest that the issues they represent are conceptually irrelevant. Instead, it shows that these items did not function statistically as part of the final retained factor structure in this sample. Some of these items may be better treated as separate indicators or as subdimensions in future instrument development.

The refined factor structure provides the empirical basis for the revised AI QMS integration model. The model retains the eight capability areas identified in earlier conceptual work but now uses a revised item structure based on results from factor analysis and reliability testing. This revised structure (see Figure 1) is presented as the main contribution of the validation process.

6.6 Intercorrelation Between the Constructs

The intercorrelations between the constructs were determined using Pearson correlation coefficients. Table 22 shows the correlations (significance at $P \leq 0.05$).

Table 22: Correlations between constructs

Variable	Marked correlations are significant at $p < .05000$; N=60 (Casewise deletion of missing data)
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	AI QMS INT	SPTot	ALTot	EDTot	TLTot	AETot	RBTot	EITot	ICTot
AI QMS INT	1.0000	.2931	.0424	.1292	.1198	.0369	.4358	.2849	.3483
		p=.023	p=.748	p=.325	p=.362	p=.780	p=.001	p=.027	p=.006
SPTot	.2931	1.0000	.7289	.6286	.1666	.6080	.4617	.2781	.4409
	p=.023	p=---	p=.000	p=.000	p=.203	p=.000	p=.000	p=.031	p=.000
ALTot	.0424	.7289	1.0000	.5949	.2335	.5276	.3243	.2245	.4488
	p=.748	p=.000	p=---	p=.000	p=.073	p=.000	p=.011	p=.085	p=.000
EDTot	.1292	.6286	.5949	1.0000	.3510	.6419	.3824	.3168	.4891
	p=.325	p=.000	p=.000	p=---	p=.006	p=.000	p=.003	p=.014	p=.000
TLTot	.1198	.1666	.2335	.3510	1.0000	.3569	-.0781	.0762	.1140
	p=.362	p=.203	p=.073	p=.006	p=---	p=.005	p=.553	p=.563	p=.386
AETot	.0369	.6080	.5276	.6419	.3569	1.0000	.4424	.0963	.3217
	p=.780	p=.000	p=.000	p=.000	p=.005	p=---	p=.000	p=.464	p=.012
RBTot	.4358	.4617	.3243	.3824	-.0781	.4424	1.0000	.4020	.6191
	p=.001	p=.000	p=.011	p=.003	p=.553	p=.000	p=---	p=.001	p=.000
EITot	.2849	.2781	.2245	.3168	.0762	.0963	.4020	1.0000	.4529
	p=.027	p=.031	p=.085	p=.014	p=.563	p=.464	p=.001	p=---	p=.000
ICTot	.3483	.4409	.4488	.4891	.1140	.3217	.6191	.4529	1.0000
	p=.006	p=.000	p=.000	p=.000	p=.386	p=.012	p=.000	p=.000	

The correlation matrix revealed several noteworthy patterns among the predictor variables. As expected, Strategic Planning (SPTot) demonstrated strong positive associations with Literacy and Competence Development (ALTot; $r=0.73$, $p<0.001$), Ethics and Data Privacy (EDTot; $r=0.63$, $p<0.001$), and Assessment and Evaluation (AETot; $r=0.61$, $p<0.001$), suggesting that institutions with clear strategic direction also tend to invest in training, ethical safeguards, and evaluative practices. Likewise, Interdisciplinary Collaboration (ICTot) correlated highly with ALTot ($r=0.45$, $p<0.001$) and EDTot ($r=0.49$, $p<0.001$), reflecting the interconnectedness of technological infrastructure and competence development. Research and Big Data Analytics (RBTot) showed a moderate positive correlation with AI QMS integration ($r = .44$, $p = 0.001$), whereas Environmental Impact (EITot) and Teaching and Learning (TLTot) exhibited weaker associations, indicating more peripheral roles in the current dataset.

6.7 Significance of regression weights of constructs

Multiple regression was used to determine the significance and regression weights of the constructs. Table 23 shows the regression results.

Table 23: Multiple regression

	b*	Std.Err. (of b*)	b	Std.Err. (of b)	t(51)	p-value
Intercept			0,409	0,873	0,469	0,641
SPTot	0,528	0,183	0,475	0,164	2,890	0,006

ALTot	-0,365	0,169	-0,363	0,168	-2,161	0,035
EDTot	-0,081	0,170	-0,068	0,141	-0,479	0,634
TLTot	0,305	0,127	0,267	0,111	2,409	0,020
AETot	-0,390	0,171	-0,440	0,193	-2,283	0,027
RBTot	0,456	0,163	0,499	0,179	2,793	0,007
EITot	0,024	0,129	0,021	0,111	0,186	0,853
ICTot	0,117	0,158	0,132	0,178	0,740	0,463
Multiple R = 0,630; R ² = 0,397; adjusted R ² = .303; F(8,51) = 4,200; p = 0,001; Std.Err. of Estimate = 1,041						

The multiple regression analysis examined the influence of eight organisational factors on AI QMS outcomes. The model was statistically significant, $F(8,51) = 4.20$, $p = 0.001$, and accounted for approximately 39.7% of the variance in AI QMS scores ($R^2 = 0.397$; adjusted $R^2 = 0.303$). This level of explanatory power is considered moderate and acceptable within social science research contexts.

Strategic Planning (SPTot) emerged as the strongest positive predictor ($\beta = 0.528$, $p = 0.006$), meaning that institutions perceived as more deliberate in planning, leadership and resourcing were also rated more highly on AI QMS integration. Research and Big Data Analytics (RBTot) also contributed positively ($\beta = 0.456$, $p = 0.007$), followed by Teaching and Learning (TLTot), which contributed positively ($\beta = 0.305$, $p = 0.020$), underscoring that research-related AI governance and pedagogical applications of AI were associated with stronger perceived AI QMS integration. In contrast, Literacy and Competence Development (ALTot; $\beta = -0.365$, $p = 0.035$) and Assessment and Evaluation (AETot; $\beta = -0.390$, $p = 0.027$) demonstrated significant negative associations. These counterintuitive findings may reflect multicollinearity among predictors, where overlapping variance suppresses or reverses expected effects.

Other variables, including Ethics and Data Privacy (EDTot), Environmental Impact of AI Technologies (EITot), and Interdisciplinary Collaboration (ICTot), did not show a statistically significant direct association in this model. The results highlight the positive contribution of strategic planning, pedagogical AI use, and research-related AI governance, while also pointing to more complex relationships involving AI literacy and assessment.

Interpret the regression results with caution, particularly for ALTot and AETot, where the coefficients were negative. The correlation results show that several constructs are strongly related to one another, which may have affected the direction and strength of some regression coefficients. The AL and RB subfactors shown in Figure 1 come from the EFA refinement process. They are included to show how the model was refined, but they were not tested as separate predictors in the regression, which used the composite construct scores. Future analyses should address multicollinearity through factor reduction or model refinement to clarify these relationships.

Figure 1 summarises the factors, their reliability, and the variance each explains. It also shows the significance and beta values for each factor.

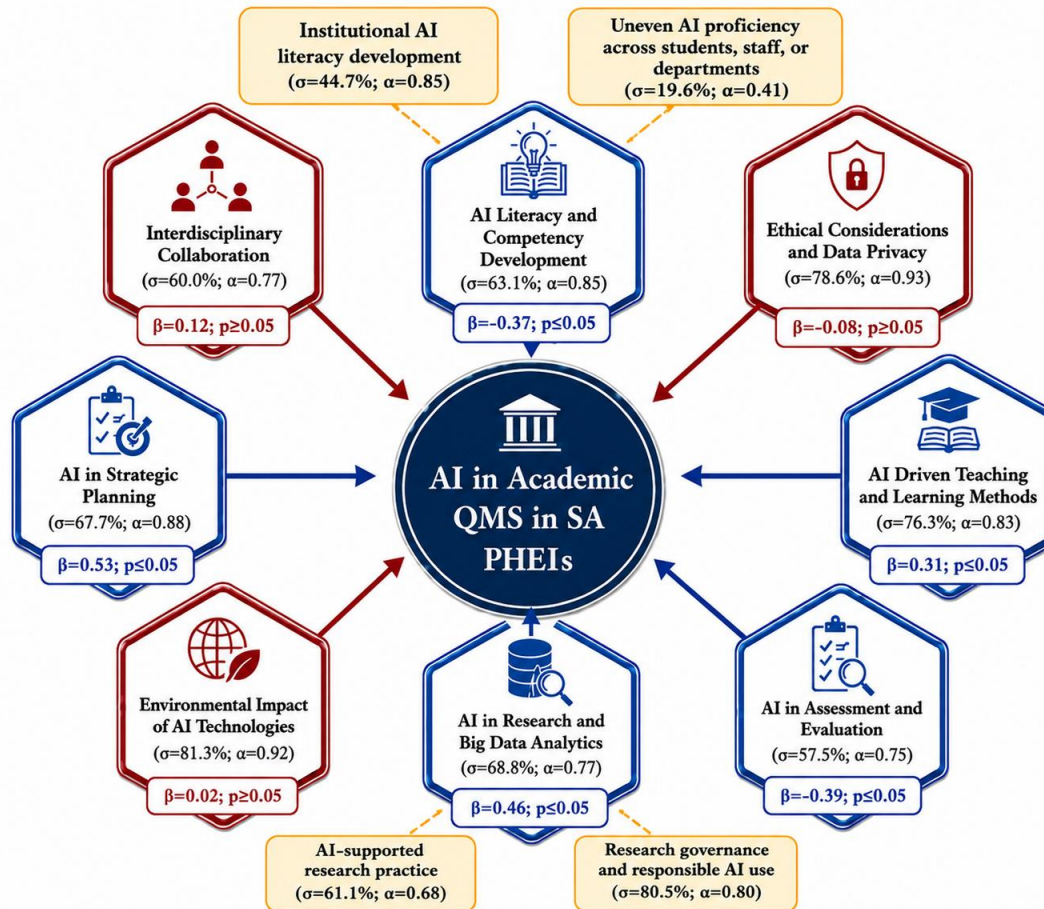


Figure 1: An empirically validated model of AI in Academic Quality Management Systems

7. DISCUSSION

This study aimed to provide evidence and refine the proposed AI QMS integration model. The results indicate that the original conceptual model was broadly defensible, but not in its initial measurement form.

The KMO and Bartlett results confirmed that all proposed constructs were suitable for factor analysis. The reliability results showed acceptable to excellent internal consistency across the constructs. However, the exploratory factor analysis demonstrated that several constructs required item-level refinement before they could be retained as part of an empirical measurement structure. This distinction is important. The model was not accepted simply because it was conceptually persuasive or grounded in qualitative findings. Instead, it was tested against empirical data and adjusted as the evidence required. The outcome is not an unchanged confirmation of the original framework. Rather, it is a refined AI QMS integration model with a clearer measurement structure.

This result is appropriate for a field that is still developing. AI integration into academic quality management remains unsettled, particularly within South African private higher education. The Council on Higher Education's Quality Assurance Framework emphasises institutional responsibility, internal quality assurance, evidence, self-regulation, and accountability (CHE, 2022). Within this context, a model for AI QMS integration must do more than list possible areas of AI use. It should provide a structured approach for identifying the institutional capabilities needed to manage AI responsibly within academic quality systems.

7.1 Stable constructs retained without modification

Three constructs were retained without any item removal: AI in Strategic Planning, Ethics and Data Privacy, and Environmental Impact of AI Technologies. These constructs showed clear factor structures and acceptable reliability, suggesting they are coherent components of the AI QMS integration model. AI in Strategic Planning remained a stable construct. This is significant because strategic planning marks the point at which AI moves from isolated tool use to institutional quality management. In the South African higher education context, the CHE's QAF requires institutions to demonstrate that quality assurance is linked to planning, evidence, and institutional improvement (CHE, 2022). The stability of this construct supports the argument that AI integration should be placed within institutional direction, leadership intention, and resource planning, rather than being treated only as an operational technology matter.

Ethics and Data Privacy were also retained without modification. This is one of the strongest outcomes of the validation process, since ethics, privacy, and accountability are central to the responsible use of AI in higher education. The Protection of Personal Information Act is directly relevant because AI systems may collect, store, process, and interpret personal information. Mbonye et al. (2024) show that POPIA applies to privacy risks arising from AI adoption, but that legal compliance alone does not resolve all governance concerns. This supports retaining Ethics and Data Privacy as a core component of the model. The Environmental Impact of AI Technologies was the third construct retained unchanged. This matters because environmental sustainability is often treated as peripheral in AI governance discussions.

The descriptive results suggested weaker institutional maturity in this area, but the EFA showed that the items formed a coherent factor. This suggests that environmental impact may be underdeveloped in practice, yet still measurable as part of AI QMS integration.

Recent African higher education research similarly notes that AI adoption is shaped by infrastructure, sustainability, and institutional preparedness concerns, especially in resource-constrained contexts (Maluleke, 2025). Together, these three stable constructs provide a strong core for the model. Strategic planning provides institutional direction, ethics and data privacy offer governance control, and environmental impact extends the model into sustainability stewardship.

Their stability supports the argument that AI QMS integration is not only a technological issue but also an institutional management concern.

7.2 Constructs refined through item removal

AI Literacy and Competency Development, AI in Teaching and Learning, and Interdisciplinary Collaboration were retained in refined form. These refinements do not weaken the model. Instead, they make it more precise. We refined AI Literacy and Competency Development by removing AL2 and AL7. These items addressed differences in AI proficiency between students, staff, and departments. Their removal does not mean that proficiency gaps are unimportant. Rather, the EFA suggests that those items measured uneven capability across groups, not the core construct of institutional AI literacy development. The retained items focus more directly on training, professional development, prompting confidence, ethical literacy, and continuous learning. This is consistent with recent AI literacy scholarship, which understands AI literacy as a combination of knowledge, skills, confidence, ethical awareness, and responsible application (Ng et al., 2024). AI in Teaching and Learning was refined by retaining TL1, TL2, and TL3. These items captured AI's pedagogical contribution, including personalisation, student engagement, student thinking, and innovative learning design. TL4 and TL5 were removed from the main factor because they reflected responsible student use and ethical classroom integration. These remain important issues, but they appear closer to responsible use governance than to the core pedagogical value of AI. The refinement, therefore, separates AI's teaching and learning contribution from the governance conditions needed to support responsible use. Interdisciplinary Collaboration was retained after IC4 was removed. IC4 was framed as a barrier statement, focusing on limited collaboration as a barrier to progress, rather than directly measuring collaborative capability. The retained items measured collaboration more directly through academic, IT, and quality assurance involvement, cross-functional teamwork, external partnerships, and the view of AI as both a technological and social innovation. This improves the

construct by separating collaboration capability from the consequences of poor collaboration. The refinements show that the model is strongest when it distinguishes between a capability and a related condition or barrier. For example, AI literacy is not the same as uneven proficiency. Pedagogical AI use is not the same as responsible use governance. Collaboration capability is not the same as the absence of collaboration barriers. These distinctions strengthen the revised model.

7.3 Complex constructs and subfactor behaviour

Assessment and Evaluation and AI in Research and Big Data Analytics produced the most complex patterns in the analysis. Both areas remained important to the model, but the factor results indicated that they should not be interpreted as broad, undifferentiated constructs. In the case of Assessment and Evaluation, AE1 was removed because it addressed the dependability of AI detection tools, while the remaining items dealt more directly with institutional assessment practice, including policy revision, assessment redesign, grading fairness, authorship and academic integrity guidance. The distinction is important because trust in AI detection tools reflects a specific and contested technical concern, rather than the wider institutional capacity to govern assessment in an AI-enabled environment.

By removing AE1, the construct became more focused on assessment governance and readiness, without allowing AI detection reliability to stand in as a proxy for assessment capability more generally. This finding is consistent with current concerns in higher education. AI detection tools remain contested because their accuracy, fairness, and procedural reliability remain unsettled. Dalalah and Dalalah (2023) argue that reliance on AI detection can create educational and ethical problems, and that institutions should focus on stronger assessment design rather than detection alone. In this context, the EFA result is conceptually defensible. AI detection reliability may need to be treated as a separate risk indicator or future subdimension, rather than combined with the broader assessment factor. AI in Research and Big Data Analytics required the strongest refinement. The retained items, RB4, RB5, and RB6, produced a narrower factor focused on institutional research governance, responsible AI data practice, and the complementary role of human expertise. RB1, RB2, and RB3 were not retained in the factor. These items relate to AI-supported research activity, including literature synthesis, verification of AI-generated outputs, and data analysis rigour. The EFA therefore suggests that research support activity and research governance should not be forced into a single construct at this stage. This refinement is secure because AI in research is not a single activity. It includes tool-assisted literature work, data analysis, output verification, research ethics, institutional policy, and human oversight. The retained RB factor is narrower than the original construct, but it is also more coherent. It is best interpreted as responsible AI research governance, rather than as the full domain of AI-supported research practice. The behaviour of Assessment and Evaluation and AI in Research and Big Data Analytics supports a key argument of this article. Some areas of AI QMS integration are too complex to be measured as broad, simple constructs. Assessment and research both involve overlapping concerns about integrity, policy, judgement, evidence, tools, and human oversight. The validation process, therefore, shows where future subfactor development may be needed.

7.4 Implications for model development

The validation process shows that AI QMS integration is better represented as a refined capability model than as a flat list of themes. The original model identified important areas, but the empirical results show that these areas do not all behave in the same way. Some constructs were stable, some required refinement, and others showed signs of greater complexity. The three broad capability domains remain useful as organising categories because they help explain how the refined factors relate to academic quality management. Interpretive Governance includes strategic planning and collaboration. Ethical Regulatory Infrastructure includes ethics, data privacy, environmental impact, and responsible research governance. Operational Capability includes AI literacy, teaching and learning, and assessment practice. However, these domains should be presented as conceptual organising domains, not as statistically confirmed higher-order constructs, unless they are tested in a separate analysis. This distinction is important. The quantitative results support the refined item structure of the eight capability areas. They do not, on their own, prove the three domains as second-order statistical constructs. The contribution is therefore more careful and defensible: the model retains the core capability areas developed in the earlier phase but now presents them in a more coherent structure.

Regression and PLS SEM outputs were considered as supplementary diagnostic evidence but were not used as the primary basis for model validation. Given the purpose of this article, the EFA and reliability results carry the main evidentiary weight. Further relationship testing and practical application of the model are therefore reserved for subsequent empirical work. This more refined model responds to a need in the higher-education AI landscape. Recent African higher education research shows that AI adoption offers opportunities in teaching, learning, administration, and access, but is constrained by academic integrity risks, privacy concerns, digital inequality, and institutional preparedness gaps (Maluleke, 2025). The revised model provides a structure for organising these concerns within academic quality management, rather than treating them as disconnected implementation issues.

8. LIMITATIONS

The findings of this study need to be read within the boundaries of the research design. The study did not set out to produce statistically generalisable claims about all South African private higher education institutions. It used purposive sampling, which enabled the researcher to recruit participants who were closely aligned with the issue under investigation. That choice was useful for an exploratory validation study, but it also means that the findings reflect the views of the stakeholder group that participated, rather than the sector. The value of the results lies mainly in refining the proposed model and in the insight gained from this sample.

The sample size also limits interpretation. The data were adequate for exploratory factor analysis at the construct level, and the KMO and Bartlett's test results supported the dataset's suitability for this purpose. Even so, the sample remains relatively small for more robust model testing. The refined factor structure should, as such, not be treated as final. A larger dataset would enable testing the structure with greater confidence and move beyond exploratory validation towards confirmatory analysis.

Survey data also introduced a limitation. Participants reported their own perceptions, experiences and levels of awareness. In fields such as AI integration, these perceptions may not always align with actual institutional practice. Some respondents may have had direct exposure to AI-enabled systems, while others may have responded from a more general understanding of AI use in higher education.

Responses may also have been shaped by institutional positioning, confidence levels, or a desire to present one's institution or professional role favourably. This is a known concern in self-report research, where participants may frame their answers in ways they regard as socially acceptable or desirable (Podsakoff et al., 2003).

Another boundary of the study is its cross-sectional design. The research captured stakeholder views at one point in time. This is useful for establishing an initial picture of AI integration into academic QMS, but it cannot show how institutional practices develop over time. This matters because AI adoption in higher education is still changing quickly. Policies, assessment practices, staff capability, governance arrangements and quality assurance processes are likely to mature unevenly across institutions. Cross-sectional research provides a snapshot, whereas longitudinal designs are better suited to tracing change and development over time (Wang & Cheng, 2020).

The study also stopped short of statistically confirming the broader capability domains as second-order constructs. These domains helped to organise the refined model conceptually, but the present analysis did not establish whether they operate statistically as higher-order dimensions. Further testing would be needed before making that claim. Future studies could use confirmatory factor analysis or structural equation modelling to examine whether the domains hold together in that way. Regression or PLS-SEM could also be used more fully to test how the refined constructs relate to the AI QMS integration outcome and whether the model has diagnostic value for institutions.

Further research should apply this model across a wider range of institutional settings. A larger sample would allow comparison between private and public higher education institutions, across different provider sizes, maturity levels, and stakeholder groups. There is also room to revisit items removed during the factor refinement process. Areas such as AI detection dependability, AI proficiency gaps, responsible student use and AI-supported research activity may still be important. Their removal from the retained structure does not mean that they lack conceptual value. It

only shows that, in this dataset, they did not behave as part of the final factor structure. Later studies may need to treat these areas as separate subdimensions or develop them further through additional item design.

9. FUTURE RESEARCH

The refined AI QMS integration model now needs to be tested beyond the exploratory sample used in this article. A logical next step would be confirmatory testing with a larger sample to determine whether the factor structure holds across different institutional settings and stakeholder groups. This is important because exploratory factor analysis identifies a possible structure, while later confirmatory work tests whether that structure is stable in other samples (Schreiber, 2021; Ferrando & Lorenzo-Seva, 2018).

The model should also be applied within institutional settings to assess its usefulness for academic quality management practice. In the South African private higher education context, this could involve using the refined constructs to identify strengths, weaknesses, and areas for improvement in AI integration. Comparative work between private and public higher education institutions may also be valuable, particularly where differences in regulation, institutional capacity, governance maturity and digital infrastructure affect how AI is adopted and managed. Recent work on AI in higher education continues to show that institutional context and governance readiness shape AI uptake in practice (Maluleke, 2025; Mogoale, 2025).

Longitudinal research would add another layer of insight. AI use in higher education is changing quickly, and a cross-sectional study can only capture perceptions at one point in time. Tracking the same or similar institutions over time would enable examination of how AI literacy, assessment practice, research governance, ethical oversight, and interdisciplinary collaboration develop as policies and quality systems mature. This would address a known limit of cross-sectional designs: their limited ability to show change over time (Wang & Cheng, 2020).

Further work is also needed on the items removed during factor refinement. The removed items should not be treated as irrelevant. AI proficiency gaps, responsible student use, AI detection reliability and AI-supported research activity remain important in the wider AI QMS landscape. In this study, they did not function as retained factors. Future instrument development could therefore test whether these areas operate better as separate subdimensions or supporting indicators. This aligns with EFA guidance that item removal is part of an iterative measurement development process, rather than a final judgement on the value of the underlying issue (Schreiber, 2021).

Finally, the collaboration dimension warrants further attention. AI QMS integration cannot be developed only by academic managers or technologists. It requires input from quality assurance practitioners, academic leaders, IT specialists, ethicists, students, policy actors and education technology partners. Roche, Wall and Lewis (2023) make a related point in arguing that AI ethics discussions need broader and more inclusive participation, especially from underrepresented contexts and groups. Future research should then examine how these different voices can be built into institutional AI governance and academic quality management processes.

10. SUMMARY

The article set out to validate and refine a proposed AI QMS integration model for South African private higher education institutions. The model had been developed from earlier conceptual and qualitative work but still needed to be tested as a measurement structure. The quantitative analysis therefore focused on data suitability, internal reliability, exploratory factor analysis, and item refinement.

The results support the model's broad structure, but not in its original form. All proposed constructs met the suitability requirements for factor analysis, and all retained constructs demonstrated acceptable to excellent reliability. However, the exploratory factor analysis showed that several constructs required refinement before they could be retained as coherent factors.

Three constructs were retained without item removal: AI in Strategic Planning, Ethics and Data Privacy, and Environmental Impact of AI Technologies. These areas showed stable factor structures and provided a strong foundation for the model. Five constructs were retained in refined form: AI Literacy and Competency Development,

AI in Teaching and Learning, Assessment and Evaluation, AI in Research and Big Data Analytics, and Interdisciplinary Collaboration. The refinements helped separate core measurement areas from related issues that may need separate treatment in future work.

The final contribution of the article is a refined AI QMS integration model. It should not be read as a predictive causal model at this stage. Its value lies in providing a clearer measurement framework for identifying the capability areas institutions should consider when integrating AI into academic quality management systems. In this way, the article moves the model from a conceptual framework toward a tested structure that can support future institutional analysis and further research.

REFERENCES

1. Ahmad, K., Iqbal, W., El-Hassan, A., Qadir, J., Benhaddou, D., Ayyash, M. & Al-Fuqaha, A.I. 2024. Data-driven artificial intelligence in education: a comprehensive review. *IEEE Transactions on Learning Technologies*, 17:12-31. doi:10.1109/TLT.2023.3314610
2. Bosch, R., Bisschoff, C., Mokoena, A. & Botha, C. 2025. AI integration in academic quality management: stakeholder perspectives from South African private higher education. *Business & IT*, XV(2):67-86. doi:10.14311/bit.2025.02.07.
3. Council on Higher Education (CHE) 2022. *Quality Assurance Framework for Higher Education in South Africa*. Pretoria: Council on Higher Education. Available at: https://www.che.ac.za/sites/default/files/publications/CHE_Quality_Assurance_Framework_2022.pdf
4. Černý, M. 2024. University students' conceptualisation of AI literacy: theory and empirical evidence. *Social Sciences*, 13(3):129. doi:10.3390/socsci13030129
5. Cortina, J.M. 1993. What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, 78(1):98-104. doi:10.1037/0021-9010.78.1.98
6. Creswell, J.W. and Plano Clark, V.L. 2018. *Designing and Conducting Mixed Methods Research*. 3rd edn. Thousand Oaks, CA: SAGE
7. Dalalah, D. & Dalalah, O.M.A. 2023. The false positives and false negatives of generative AI detection tools in education and academic research: the case of ChatGPT. *The International Journal of Management Education*, 21(2):100822. doi:10.1016/j.ijme.2023.100822
8. Dawadi, S., Shrestha, S. & Giri, R.A. 2021. Mixed-methods research: a discussion on its types, challenges, and criticisms. *Journal of Practical Studies in Education*, 2(2):25-36. doi:10.46809/jpse.v2i2.20
9. Etikan, I., Musa, S.A. & Alkassim, R.S. 2016. Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1):1-4. doi:10.11648/j.ajtas.20160501.11
10. Ferrando, P.J. & Lorenzo-Seva, U. 2018. Assessing the quality and appropriateness of factor solutions and factor score estimates in exploratory item factor analysis. *Educational and Psychological Measurement*, 78(5):762-780. doi:10.1177/0013164417719308
11. Ferrando, P.J., Morales-Vives, F., Casas, J.M. & Muñoz, J. 2025. Likert scales: a practical guide to design, construction and use. *Psicothema*, 37(4):1-15. doi:10.70478/psicothema.2025.37.24
12. Field, A. 2017. *Discovering statistics using IBM SPSS statistics*. 5th edn. London: SAGE Publications.
13. Hair, J.F., Black, W.C., Babin, B.J. & Anderson, R.E. 2019. *Multivariate data analysis*. 8th edn. Andover: Cengage Learning.
14. Jebb, A.T., Ng, V. & Tay, L. 2021. A review of key Likert scale development advances: 1995-2019. *Frontiers in Psychology*, 12:637547. doi:10.3389/fpsyg.2021.637547
15. Maluleke, A.F. 2025. AI adoption in African higher education: a systematic review of benefits and ethical implications. *Interdisciplinary Journal of Education Research*, 7(2). doi:10.38140/ijer-2025.vol7.2.05
16. Mbonye, V., Moodley, M. & Nyika, F. 2024. Examining the applicability of the Protection of Personal Information Act in AI-driven environments. *South African Journal of Information Management*, 26(1):a1808. doi:10.4102/sajim.v26i1.1808
17. Mogoale, P.D., Pretorius, A., Mogase, R.C. & Segooa, M.A. 2025. Integrating artificial intelligence within South African higher learning institutions. *South African Journal of Information Management*, 27(1):a1939. doi:10.4102/sajim.v27i1.1939
18. Ng, D.T.K., Wu, W., Leung, J.K.L., Chiu, T.K.F. & Chu, S.K.W. 2024. Design and validation of the AI Literacy Questionnaire: the affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, 55(3):1082-1104. doi:10.1111/bjet.13411
19. Nguyen, A., Ngo, H.N., Hong, Y., Dang, B. & Nguyen, B.P.T. 2023. Ethical principles for artificial intelligence in education. *Education and Information Technologies*, 28:4221-4241. doi:10.1007/s10639-022-11316-w
20. Nunnally, J.C. & Bernstein, I.H. 1994. *Psychometric theory*. 3rd edn. New York: McGraw-Hill.
21. Pallant, J. 2020. *SPSS survival manual: a step-by-step guide to data analysis using IBM SPSS*. 7th edn. London: McGraw-Hill Education.

22. Patel, S. & Ragolane, M. 2024. The implementation of artificial intelligence in South African higher education institutions: opportunities and challenges. *Technium Education and Humanities*, 9:51-65. doi:10.47577/teh.v9i.11452
23. Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. & Podsakoff, N.P. 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5):879-903. doi:10.1037/0021-9010.88.5.879
24. Roche, C., Wall, P.J. & Lewis, D. 2023. Ethics and diversity in artificial intelligence policies, strategies and initiatives. *AI and Ethics*, 3:1095-1115. doi:10.1007/s43681-022-00218-9
25. Schreiber, J.B. 2021. Issues and recommendations for exploratory factor analysis and principal component analysis. *Research in Social and Administrative Pharmacy*, 17(5):1004-1011. doi:10.1016/j.sapharm.2020.07.027
26. South Africa (SA) 2013. *Protection of Personal Information Act 4 of 2013*. Government Gazette, 37067.
27. Wang, X. & Cheng, Z. 2020. Cross-sectional studies: strengths, weaknesses, and recommendations. *Chest*, 158(1S):S65-S71. doi:10.1016/j.chest.2020.03.012