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Adaptive Ai-Driven Total Quality Management for Higher Education Excellence

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Abstract

Purpose: The rapid technological evolution, student population diversity and stakeholder expectations are contemporary challenges of universities. Consequently, higher education institutions need to adopt a more flexible, data-oriented, and responsive quality management approach. TQM has been in existence for many years in the higher education industry, but the PDCA design-based quality cycles are typically back looking, not integrated and slow. The PDCA design-based quality cycles happen at the school and administrative unit levels. While learning analytics, predictive modelling, and process automation have been deployed regularly, they are mostly in piecemeal and narrow contexts.

Methodology: This review systematically examines 74 peer-reviewed studies published between 2019 and 2025. These studies are indexed by Web of Science and Scopus. Above all, it explores how AI and TQM are increasingly converging. In short, this is happening at the intersection of higher education quality management. The study primarily aims to investigate key implementation issues, delin-eate AI-enabled quality practices, and identify opportunities of using AI in PDCA cycle.

Findings: The lack of real-time feedback and adaptive response systems. Systemic disconnect in the data systems of the academic and administrative departments. Slow intervention due to inflexible PDCA cycles. These are the major perils identified in the review. Such challenges limit the agility of higher education institutions in responding to student needs, quality risks and institutional performance deficits. In response, this review suggests an Adaptive AI-Driven TQM Cycle which proposes to embed Real-time analytics, predictive modelling, automated interventions and continuous stakeholder feedback at every stage of PDCA.

Recommendations: According to the proposed model, higher education leaders can make use of an evidence-based framework to develop an agile, transparent, and student-centred quality management system. The future implementation should consist of integrated institutional data systems, ethical governance of AI, building the capacity of staff, and ongoing evaluation of the quality improvement practices supported by AI. Enhanced student retention, satisfaction, responsiveness to institutions, and long-term competitiveness can be supported by this approach.

Keywords: *Artificial Intelligence (AI); Total Quality Management (TQM); Higher Education Quality Management; Predictive Analytics; Adaptive AI-Driven PDCA; Quality 4.0; Quality 5.0; AI Governance*

JEL Classification Codes: I23; M15; M10; O33; C55

INTRODUCTION

Higher education institutions are now facing period of rapid change in terms of technological acceleration, student population growth, and an increased expectation from (employers, policymakers, ad society). Because of these rapid changes, universities are under strong pressure to improve their overall performance (Acharya et al., 2025; Kadri et al., 2022). Therefore, quality is no longer seen as a supporting function only; it has become a strategic issue that affects student (satisfaction, graduate outcomes, institutional reputation, and long-term sustainability). To respond to these pressures many universities have adapted structured quality management (SQM) approach to support continuous improvement and strengtheninstitutional performance (Girón et al., 2023; In'airat & Kassem, 2014; Yusuf, 2023). Among the available management approaches, Total quality management (TQM) remains one of the most recognised frameworks in higher education institutions. TQM utilised due its capability to provides a border institutional philosophy that focuses on stakeholder needs, continuous improvement, teamwork, process integration, and evidence-based decision making (Ibidunni et al., 2023).

In universities this means improving (teaching, learning, administration, student services, and governance) in an organised and continuous way. Didham & Ofei-Manu, (2020) and Setyadi et al. (2025) studies show that TQM can improve (operational efficiency, student satisfaction, and institutional capacity) for innovation and risk management. While, Catanzano et al. (2022) found that embedding TQM principles into curriculum design, faculty development, and resource planning can improve student retention, graduate employability and institutional reputation. Besides, Anastasiou & Ntokas, (2024) and Kayyali, (2024) studies from European universities showed that TQM can strengthen collaboration across academic units and improve transparency and accountability in governance structures. Their findings can confirm that TQM continues to be relevant as both a management tool and a guiding philosophy for universities operating in a complex and changing environment (Kayyali, 2024; Tabish, 2024).

Even at first TQM was first developed in industrial and service settings it has been showing successful adaptation to higher education settings. In factory settings it uses to improve factory productivity and service efficiency through Plan-Do-Check-Act (PDCA) cycle, besides to quality circles and continuous process control. On the other hand, in universities it has been reinterpreted as framework for improving across the whole institution (Chigbu & Makapela, 2025). In practice higher education institutions have borrowed several ideas from industry sittings such as, 5S organization, consumer focus and standardised quality control; they were applied to educational areas such as student onboarding, administrative workflow re-design, and library service improvement. These efforts were often supported by audit mechanisms inspired by ISO 9001 (Walawalkar et al., 2024). According to (Gardezi, (2024) and Zabalawi et al. (2024) many universities have established quality improvement teams made up of faculty members administrative staff and student representatives to indemnify and test pilot interventions and evaluate outcomes using key performance indicators (KIPs).

Empirical support evidence has been reposted for the use of TQM in higher education institutions. Where, institutional gains have been observed in (student satisfaction, administrative efficiency, research productivity, curriculum alignment, and stakeholder trust) when TQM principles have been implemented Tropea, (2018) found a 22% increase in student satisfaction, 17% reduction in administrative cycle time, and a 14% increase in research output per faculty after TQM based re-structuring approach was adapted in North America and Europe universities. In Aisa and Africa setting Awashreh (2025) found that after using industrial risk management tools the service interruptions reduced up to 32% leading to trust improvement among external stakeholders.

In curriculum design setting the using of Define, Measure, Analyse, Improve, and Control (DMAIC) method was associated with a 16% improvement in licensure pass rates and a 12% increase in employment satisfaction with graduate readiness (Monday, 2022; Yelamarthi et al., 2025). Gami et al. (2024) utilised real time monitoring through balanced scorecards (BCs) and dashboards to support faster and more informed decision making in higher education settings. In contrast, Ezzaim et al. (2024) reported a strong and statistically significant effect of TQM on higher education institutions performance with an average effect meta-analysis size of $r = 0.87$, and $p < 0.001$ across major institutional outcomes.

On the other hand, AI has been increasingly adapted across both teaching and administrative functions in higher education institutions, AI tools such as, machine learning (ML), predictive analytics (PA), natural language processing (NLP), and robotic process automation (RPA) are now begin used to improve higher education institutions responsiveness, personalisation and efficiency (George & Wooden, 2023; Han et al., 2025; Murdan & Halkhoree, 2024). AI based pattern detection enabled early identification of at-risk students reduction of up to 25% (Al-Shabandar et al., 2019; Nimy et al., 2023). Besides, Boatman, (2021) reported that the personalised learning pathway also been supported though recommender systems with effective sizes of $d = 0.5$ to 0.7.

In administration settings, processing time has been reduced by more than 60% through RPA while NLP-based chatbots have resolved nearly 80% of routine enquiries with a statistically significant levels above 85% (Adam et al., 2021; Merga & Mason, 2021). Border AI ecosystems have further been associated with 15% gains in retention, 12% gains in graduation rates and a 20% reduction in administrative overhead cost (Acharya et al., 2025; Al-Shabandar et al., 2019; Gardezi, 2024). However, trust in AI systems has been shown to depend on transparent governance, audit procedures, and consent mechanisms (Didham & Ofei-Manu, 2020; Ezzaim et al., 2024; Mazher, 2025).

Despite the value of TQM and AI their development in higher education institutions had largely been carried out in parallel rather than through integration. TQM has continued to rely mainly on periodic audits, end of term surveys and fixed KPIs which are useful but mostly retrospective; as a result quality issues are often identified only after the damage already occurred (Walawalkar et al., 2024). In contrast, AI initiatives have often been implemented as isolated pilots or standalone technical solutions with limited connection to institutional quality cycles (Gami et al., 2024); because of this separation the combined value of AI and TQM has not yet been fully realised. Several unresolved challenges have therefor, remained and real time intervention is still weak, and institutional data is still fragmented across academic and administrative systems. Besides, predictive insights are still not being translated into timely and coordinated improvement actions, which resulting of an universities continue to create in data rich but insight poor condition leading to a weak continuous improvement, slows institutional learning and limits stakeholders responsiveness (Buchan et al., 2017; Knox et al., 2025; Xue & Xue, 2025).

A growing body of literature has addressed either TQM or AI in higher education, but a fully integrated perspective has rarely been provided. In some studies, only conceptual links have been suggested. For example, ChatGPT was mapped onto TQM-related functions in higher education by Utkirov (2024), but no institutional testing was reported. A roadmap linking adaptive learning, feedback, and TQM principles was proposed by Correia et al. (2024), yet empirical implementation was not provided. A more practical step was reported by Xu (2025), where AI models were deployed for management and personalised teaching, but these functions were still not embedded in a full TQM cycle.

Ezzaim et al. (2024) reviewed AI based learner profiling but limited real world validation was identified. The evolution of adaptive AI learning research was mapped by Strielkowski et al. (2025) yet live deployment and ethical control were not assessed. Chigbu and Makapela (2025) proposed feedback-oriented governance model but it was not piloted in a functioning university system. Durón and Jiménez-Preciado (2025), Khairullah et al. (2025), Alotaibi (2024) and Vera Millalén (2024) addressed generative AI, governance, adaptive learning, sustainability, and Quality 5.0 respectively; but a fully integrated and empirically grounded AI driven TQM cycle for higher education was still not presented, these differences and omissions are summarised in Table 1.

In response to these gaps, this review was designed with four objectives. First, the current integration of AI technologies into TQM-related practices in higher education was critically examined. Second, the major barriers that continue to limit proactive and adaptive quality improvement were identified. Third, a new Adaptive AI-Driven TQM Cycle tailored to higher education was proposed. Fourth, strategic guidance was developed for the ethical and governance-oriented integration of AI-driven adaptive mechanisms in support of student satisfaction, retention, and institutional excellence.

Table 1: Comparative Analysis of Existing Reviews on AI and TQM in Higher Education

Study	TQM Focus	AI Focus	Integrated Approach	Real-Time Analytics	Adaptive Feedback Loops	Ethical Considerations	Empirical Validation	Higher Education Context
(Ukirov, 2024)	Quality assurance, process efficiency frameworks	ChatGPT-based chatbots for instruction, grading, and support	Theoretical mapping of chatbot functions onto TQM principles; no pilot integration	-	-	Security, plagiarism, and workforce displacement	Narrative literature synthesis: no primary data collected	Broad HEI settings, framed by constructivist, socio-cultural, and cognitive theories
(Correia et al., 2024)	-	AI-driven personalisation for critical thinking	Conceptual framework combining adaptive learning paths, problem-based modules, and TQM principles (no pilot integration)	Demonstrated via real-time content adjustment	Embedded real-time, individualised feedback	Addressed fair use, data privacy, and transparency	-	Broad HEI applications focusing on critical thinking curricula
(Xu, 2025)	-	Optimisation algorithms for management and personalised teaching	Literature review, case analyses, and a semester-long deployment of AI models for scheduling, resource allocation, and tailored instruction	-	Algorithmic adjustments to learning paths driven by ongoing performance data	IRB approval, informed consent, data privacy safeguards, and bias monitoring	Quasi-experimental comparison over one semester showing boosts in engagement, outcomes, satisfaction, and efficiency	Single university setting across multiple programs
(Ezzaim et al., 2024)	-	Data-driven algorithms (Decision Trees, ANNs) for inferring individual learning styles	Systematic review of 40 WoS/Scopus articles (2014-2022) across platforms	-	-	-	-	Diverse e-learning settings, predominance of Moodle
(Strielkowski et al., 2025)	-	Bibliometric mapping of AI-driven adaptive learning trends	VOSviewer analysis of 3 518 WoS publications	-	-	-	-	Global scholarly output in education

(Chigbu & Makapela, 2025)	-	-	Conceptual model weaving data-driven decision-making with SDG alignment and systemic quality enhancement	-	✓	Data governance, equity, inclusion, balancing analytics with pedagogy	Systematic literature review; no new empirical test	Global HEIs (with insights from South African cases
(Durón & Jiménez-Preciado, 2025)	-	Trends in generative AI, LLMs, ChatGPT	Text-mining of scholarly discourse without quality cycle integration	-	-	Responsible AI use, equity in access, and digital divides	Quantitative content analysis of 52 peer-reviewed articles	Global highbred research landscape
(Khairullah et al., 2025)	-	End-to-end AI in teaching, research support, enrolment, records, and finance	Holistic embedding of AI under a governance-driven leadership model	✓	✓	Bias mitigation, data privacy, job-displacement risks	-	Global HEIs (Asia, Middle East)
(Alotaibi, 2024)	-	Personalisation via AI agents, adaptive assessments, analytics	AI modules are woven directly into the LMS to support sustainability goals	✓	✓	Data privacy, algorithmic bias, equity	-	Global HE (focus Saudi Arabia)
(Maljugić et al., 2024)	Conceptual Quality 5.0 model for Society 5.0	Human-centric digital technologies (IoT, AI, cloud)	Synthesis of quality management, Society 5.0 principles and advanced tech	-	✓	Sustainability & social equity	✓	✓

(Vera Millalén, 2024)	-	Adaptive AI-driven personalisation and real-time learning	Embedding AI systems into course delivery and assessment	✓	✓	Data privacy, algorithmic bias mitigation	Likert survey of nursing faculty	Private university nursing program in Chile

A systematic literature review (SLR) approach was adopted in this study. Peer-reviewed studies published between 2019 and 2025 were retrieved from Web of Science and Scopus using the terms "Artificial Intelligence", "Total Quality Management", "Higher Education", "Predictive Analytics", and "Student Engagement". An initial set of 465 studies was identified. These records were then screened using explicit inclusion and exclusion criteria based on relevance, methodological rigour, empirical validation, and direct applicability to higher education. To improve transparency and consistency, the review process was guided by a PRISMA-style selection logic. The full identification and screening procedure is presented in Figure 1.

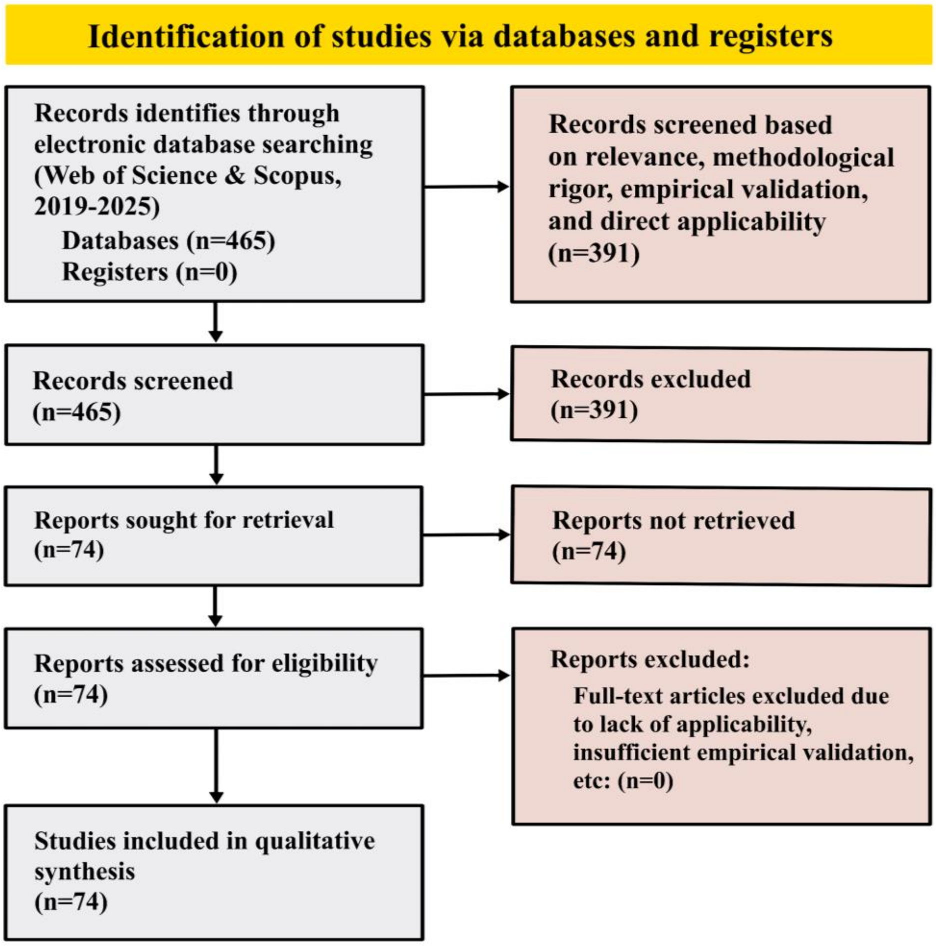


Figure 1: PRISMA-Style Study Selection Flow Diagram

Real-time predictive AI analytics have not, to the best of our knowledge, been placed directly within the classical PDCA cycle in higher education institution-specific review frameworks. This constitutes a Unique Research Contribution (URC) of this review. As a consequence, the novelty of this review does not lie in the mere discussion of AI and TQM together, but rather in showing how AI could be integrated into TQM through an adaptive, operational and human-centred quality management model.

At present, a transition from Quality 4.0 to Quality 5.0 is taking place. Quality 4.0 emphasizes digitalization, automation, big data and smart quality systems. While Quality 5.0 follows in this direction, it adds an emphasis on humanity-centred AI, governance ethics, stakeholder well-being and institutional responsiveness. In this light, with AI not being a new technology which is going to add on to the existing technology, it can strengthen the core pillars of TQM in Higher Education Institutions. To illustrate, Natural Language Processing (NLP) enables responsiveness to students 24/7 by tackling queries automatically, analysing sentiments, and quicker interpretation of student feedback thereby supporting TQM's stakeholder focus principle. In the same way, predictive analytics augments continuous improvement efforts by uncovering early risks around student retention, performance, service delays and quality gaps. Through process automation it is possible to increase efficiency as administrative errors get reduced, service consistency is maintained and routine quality processes become faster. This real-time visibility into academic and administrative performance, which the UI-ICAI project dashboards offers, also fosters leadership commitment and evidence-based decision-making.

The years 2019-2025 were selected because this is a phase of rapidly moving digital advance in higher education before, during, and after the COVID pandemic. As the year rolled on, colleges started using more online learning platforms, learning analytics, digital student services, AI-smart tools and automated administration. As such, this period is relevant for examining how AI capabilities have started to intervene in TQM practices and quality improvement models of institutions of higher education.

This review makes four main contributions. To begin with, it provides a conceptual link between AI-enabled digital transformation and TQM, two fields that have typically been taken separately in higher education studies. Moreover, it highlights some major unresolved barriers to be addressed like fragmented data systems and delayed intervention, as well as rigid quality cycles. Also, it covers weak adaptive feedback and inconsistent stakeholder engagement. A third aim of this paper is to position ethical and governance issues as central rather than peripheral in AI supported quality management. Fourth, it proposes an evidence-based Adaptive AI-Driven TQM Cycle to help higher education institutions build more agile, transparent, ethical, and student-centred quality systems. Figure 2 outlines the organization of this review paper.

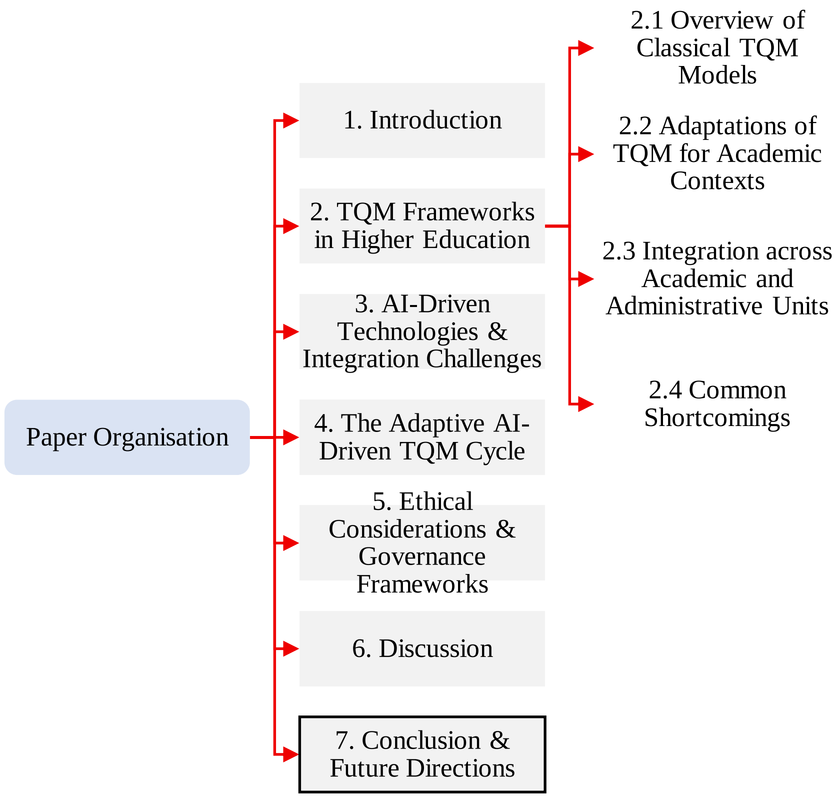


Figure 2: Proposed Review Study Organisation

TQM Frameworks in Higher Education

Overview of Classical TQM Models

The evolution of total quality management (TQM) from its early use in manufacturing to its later application in universities signals an important change in quality as it has been understood. The original classical TQM models were of reaction type which are designed for relatively stable industrial environment where quality mainly related to process control error reduction standardisation defect reducing efficiency system of production. According to Agrawal (2019), and Caldwell & Varkey (2021), one of the most effective contributions was made by Deming (1991) Plan – Do – Check – Act (PDCA) cycle and his famous 14 points which are shown in Figure 3. In the Deming model, quality was defined not as a final state but a process, informed by ongoing feedback and measurement, as well as leadership commitment and institutional learning.

Notwithstanding, the traditional PDCA cycle was created for a slower quality environment where data was usually collected at intervals, assessed manually, and implemented into improvement actions after a considerable delay. In 2026, the logic will become increasingly inadequate. Universities create stream of data through learning management system, student information system, online assessment system, helpdesk system, employability portal, accreditation dashboard. In this environment, quality problems do not wait for annual reviews or end-of-semester evaluation cycles. Real time risks such as failing to engage students; dissatisfaction with courses; course service delays; drop off or failure to retain students; or negative impacts on their academic performance may arise and these need to be acted on earlier. Thus, in the contemporary higher education sector, the principal drawback of classical PDCA is not the idea of continuous improvement, but performing in a slow-going, retrospective, and piecemeal manner.

An analysis of the conventional PDCA cycle and the shift from Quality 4.0 to Quality 5.0 reveals the inadequacies of traditional PDCA in modern-day higher educational settings. Quality 4.0 refers to digital transformation, automation, data alignment, analytics, connectivity, and quality in real time. For universities, this direction is evident in the increasing usage of AI, LMS integration, digital platforms, and data-driven institutional management (Alotaibi, 2024; Zabalawi et al., 2024). The concepts of Quality 5.0 extend this digital logic. It emphasises human-centred AI, ethical governance, stakeholder well-being and sustainability, and responsible decision-making. All are becoming more relevant in contemporary quality management systems (Khairullah et al., 2025; Maljugić et al., 2024).

A conventional PDCA cycle based primarily on delayed reporting, manual audits and periodic committee meetings does not seem to be able to respond adequately to the speedy, complexity and human-centred expectations of higher education quality management. Researchers have recently conducted studies on AI-enabled higher education and institutional transformation. The application of data-driven decision making, digital learning systems, predictive analytics and responsible AI leadership is becoming necessary to enhance institutional responsiveness, quality maturity and strategic governance (George & Wooden, 2023).

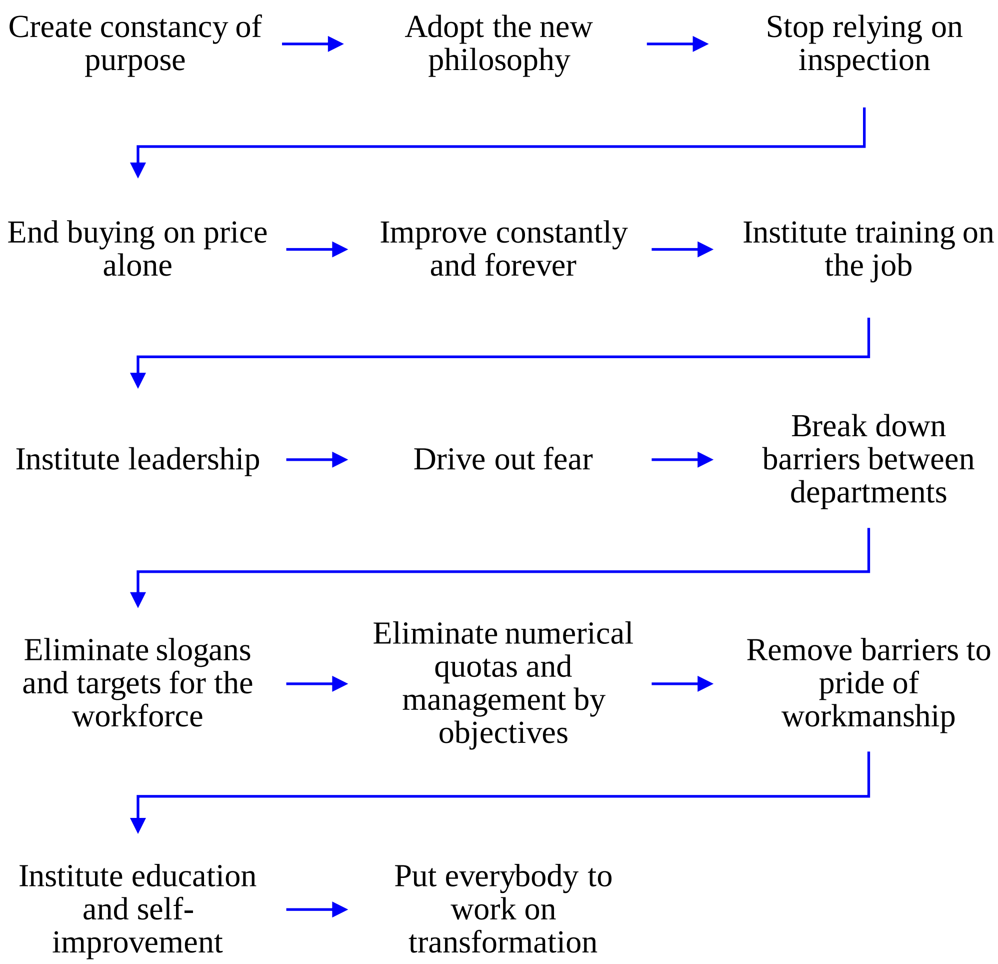


Figure 3: Deming's Quality Principles

The quality trilogy of Juran (1992), which emphasised greater managerial responsibility, quality planning and choice of the organisational processes to meet stakeholder requirements, strengthened this foundation. The zero-defects orientation sought prevention rather than correction by insisting on clear standards, process discipline, and strong conformity to requirements (Goetsch & Davis, 2005; Zhou et al., 2025). The traditional approaches contributed significantly to quality thinking and produced impressive outcomes in both industrial and service environments. Nevertheless, the direct transfer of these graduates took a tortuous route. According to the UK Quality Assurance Agency (QAA), 2018-19 has been a year when 'universities are not factories, and we cannot measure educational quality along linear processes, defect-based indicators or doing what it says on the tin.' Human interaction, academic freedom, diversity within institutions, complexity of educational processes, stakeholder expectations and conflicts, as well as changing needs of learners shape higher education. According to In'airat and Kassem (2014), Jasti et al. (2021), and Yusuff (2021), classical models of TQM require contextual adaptation to support quality improvement in universities.

Furthermore, the PDCA classical model does not adequately explain how digital quality signals should be translated into timely academic and administrative action. When students stop accessing the learning management system, consistently miss online quizzes, submit assignments late or lodge service complaints yet to be resolved, they may be exhibiting signs of disengagement. A classic phase of checking being done at semester end may only catch this issue when the opportunity to intervene meaningfully is already gone. On the contrary, learning analytics and early warning systems powered by artificial intelligence are capable of detecting academic risk earlier on through the analysis of data from engagement, attendance, assessment, and progression (Al-Shabandar et al., 2019; Nimy et al., 2023). Learning analytics as personalised feedback to improve student understanding of their learning progress, given that information is provided to students at the right time and in an understandable way (Baig & Yadegaridehkordi, 2024). Nevertheless, these tools are only made to create quality value when the outputs developed are tied back to actual institutional action component, such as advising, tutoring, service follow-up, curriculum review or student support intervention. This shows the necessity to transition from a periodic PDCA cycle to an adaptive AI-powered quality loop that continuously detects, interprets, acts, and learns.

Because of this, there is now recent scholarship which argues against simply transferring classical TQM models to higher education and instead adapting them to fit the context. To this end, more recent studies have revisited the major principles of classical TQM and develop more sophisticated academic interpretations by taking into consideration of the stakeholder, accreditation, governing, digital transformation and institutional performance (Cheah et al., 2023; Girón et al., 2023; Zabalawi et al., 2024). In the new understanding, core philosophy (CP), key principles (KP), and prime focus (PF), are no longer just limited to matter of efficiency and control but are expanded to pedagogic flexibility, institutional learning, student-centred improvement and digital responsiveness. In like manner, Measurement Emphasis (ME) and Quality Standards (QS) are stretched further than defect rates, operational consistency to include students learning outcomes, retention performance, graduate readiness, accreditation, real-time institutional analytics.

Moreover, the incorporation of AI should be specifically related to the core pillars of TQM, rather than considering it as an independent layer of technology. Natural Language Processing (NLP) as yet another technology can provide 24/7 query handling from students, automating the classification of positive and negative feedback, sentiment analysis and further speeding up the interpretation of complaints and service requests, thereby directly facilitating the stakeholder focus principle of TQM (Durón & Jiménez-Preciado, 2025). Predictive analytics enhances continuous improvement through the early identification of various risks, such as those associated with student retention, course performances, service delays and academic progression (Nimy et al., 2023). Process automation assists process management by diminishing repetitive administrative mistakes, enhancing turnaround time, and standardising routine quality processes (Alotaibi, 2024). The usage of AI-empowered dashboards facilitates commitment from leadership and decision-making based on evidence by allowing academic leaders to have a real-time view of performance relating to programme, course, student, and service (Han et al., 2025). In conclusion, transparent and reproducible audit trails and explainable AI promote accountability by making AI-supported decisions transparent, reviewable, and defensible on ethical grounds (Mökander & Floridi, 2023; Oncioiu & Bularca, 2025).

Table 2: Classical TQM Model Comparison

Criterion	Deming (1991)	Juran (1992)	Goetsch and Davis (2005)	Academic Adaptation	Measurement Emphasis	Leadership Focus	Employee Role
Core Philosophy	Continuous Improvement	Quality Planning & Control	Zero Defects	Learning-Cantered Improvement	Student learning outcomes, progression metrics	Shared governance	Faculty-student co-creation
Key Principles	PDCA Cycle, 14 Points	Quality Trilogy	Prevention, Standards Conformance	Agile PDCA with iterative feedback loops	Course evaluation scores, accreditation results	Distributed leadership	Collaborative curriculum teams
Primary Focus	System-wide change	Managerial accountability	Prevention focus	Pedagogical excellence, holistic student development	Retention, graduation rates	Academic council oversight	Participatory decision-making
Measurement Emphasis	Statistical Process Control	Defect Reduction	Cost of Quality (CoQ)	Mixed quantitative-qualitative (surveys, portfolios)	Learning analytics, satisfaction indices	Transformational and servant	Continuous professional development
Quality Standards	Production conformity	Customer satisfaction	Clear defect standards	Accreditation frameworks, learning outcome taxonomies	Benchmark assessments, peer reviews	Collaborative visioning	Embedded in performance evals
Leadership Focus	Transformational	Managerial ownership	Top-down strategy	Distributed, inclusive leadership	Balanced scorecards for units	Empowerment across units	Shared academic leadership
Employee Role	Integral to improvement	Active participation	Commitment & motivation	Faculty and staff as co-designers of learning experiences	Teaching quality metrics	Mentorship and facilitation	Student partners in governance
Stakeholder Inclusion	Implicit in customer focus	Limited to customers	-	Students, employers, and alums are core stakeholders	Stakeholder satisfaction surveys	Stakeholder councils	Cross-functional teams
Feedback Mechanisms	Annual review cycles	Periodic audits	Post-mortem defect analysis	Real-time course feedback, digital dashboards	Continuous formative assessment	Feedback-driven strategy	Reflexive practice groups
Cultural Adaptability	Homogeneous workforce assumption	-	-	Contextualised to institutional culture and values	Diversity and inclusion indicators	Culturally responsive leadership	Inclusive engagement methods
Sustainability Orientation	-	-	-	Integration of sustainability in curricula and operations	Environmental impact metrics	Sustainability-driven leadership	Green academia initiatives
Continuous Learning	Implied through PDCA	Implied in quality improvement	Implied in ongoing prevention	Formalised lifelong learning pathways for staff and students	Professional development hours, CPD records	Learning culture advocates	Peer learning communities

At the governance level, leadership focus (IF) also has changed. The perception of higher education quality leadership is shifting, as indicated by the emergence of shared governance frameworks that engage deans, academic leaders, faculty members, quality officers, administrative units, and student representatives instead of a managerial prerogative (Cheah et al., 2023; Hillman & Baydoun, 2019). Similarly, the traditional Employee Role (ER) has evolved into a broader concept of Faculty and Staff Engagement (FSE) where quality is supported through collaborative actions in the areas of curriculum design, student support, enhancement of services, and institutional innovation (Gamage et al., 2020; Jasti et al., 2021). Similarly, Stakeholder Inclusion (SI), Feedback Mechanisms (FMs), Cultural Adaptability (CA), and Sustainability Orientation (SO) are more recent criteria, which indicate changing priorities of universities today. These dimensions recognise the increasing significance of community partnerships, real-time feedback from students, intercultural responsiveness, and long-term institutional liability, one that encompasses environmental and social sustainability (Didham & Ofei-Manu, 2020; Girón et al., 2023; Rahman & Nasrin, 2024).

Nonetheless, these adaptations remain incomplete if they do not cover the essential digital weakness of classical PDCA, i.e. the gap between data being available and quality action being taken. Many universities now gather large amounts of data about students and their organisation, but this data is often stored in siloed systems and reviewed by different departments with limited interactivity (Alotaibi, 2024; Zabalawi et al., 2024). As a result, the various strands of quality assurance become fragmented. Belonging as they do, to academic data, administrative data, student support data and accreditation evidence, instead, they are attached as files and not as one quality intelligence system (Gamage et al., 2020; Javed & Alenezi, 2023). The result is that timely intervention is delayed, reporting is duplicated, cross-functional learning is weak or absent, and institutional memory is limited. By 2026, this fragmentation is not merely a nuisance for university operations; it hampers the institution's ability to deliver proactive, student-centred and evidence-based quality management (George & Wooden, 2023; Han et al., 2025; Khairullah et al., 2025).

To give a more flexible, contextual approach and develop a digital response which is effective for total quality management in higher education rather than a narrow industrial logic. While continuous improvement is still a mainstay, it must now be buttressed by reflexive feedback; inclusive participation; convergent analytics; and a greater emphasis on learning and institutional development (Kayyali, 2024; Yusuf, 2023). In this sense, it is not that classical TQM is rejected in higher education; rather, it is reinterpreted and expanded to suit academic life. As such integrated dimensions provide a better basis for a TQM framework for academia, it allows for sustaining logic of PDCA while embedding more responsive, student-centred, and stakeholder-driven quality loops (Cheah et al., 2023; Girón et al., 2023; Hillman & Baydoun, 2019). By having additional feedback loops and more actors linked to the classical PDCA structure, the learning organization model becomes stronger as shown in Figure 4. It is applicable in the context of Higher Education.

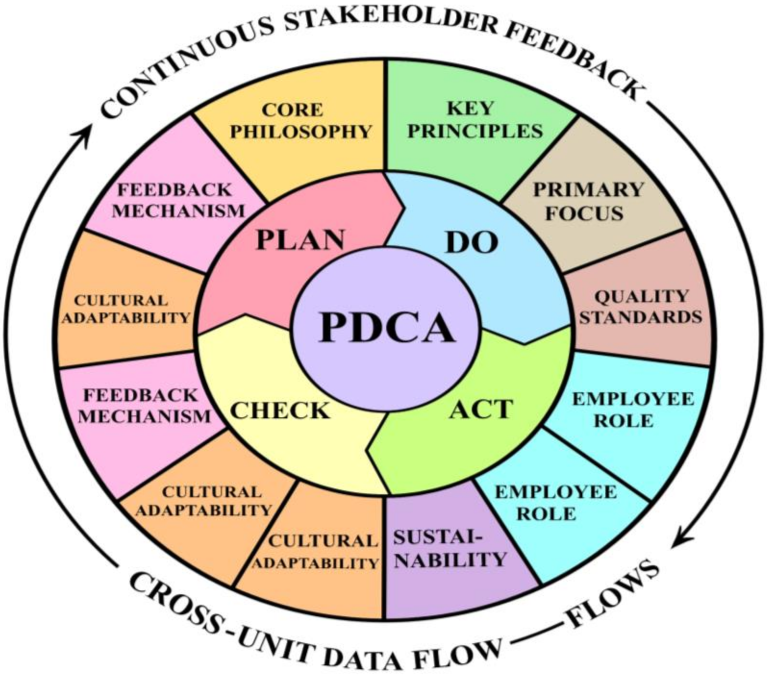


Figure 4: Adapted TQM Framework for Higher Education

Furthermore, higher education's customer focus has changed in meaning as there is a shift from a product-based view of quality to that of service and learning-centred views. At universities, quality is no longer directed toward a single end user. Instead, it is increasingly understood as multi-stakeholder engagement, where students, employers, alumni, professional bodies, accreditation agencies, and community partners play important roles in shaping quality expectations and improvement priorities (Hillman & Baydoun, 2019; Rahman & Nasrin, 2024; Yusuf, 2023). This broader orientation is echoed in surveys of satisfaction, feedback panels, measures of student experience, data on graduate employability and indicators of digital engagement to capture various forms of stakeholder experience and judgement. Likewise, the conventional notion of employee involvement has been reinterpreted in the academic context as a type of inclusive governance. The universities are encouraged to design their processes (teaching, research, and administration) collaboratively through faculty-administration committees, cross-functional quality circles and student partnership mechanisms, instead of restricting participation to operational staff (Bah et al., 2024; Jasti et al., 2021).

The measurement system at a level of evaluation in the higher education system has also become more complex. The institutions are now utilizing informal evidence, including teaching climate diagnostics, reflective practice records, student experience data, and digital engagement patterns, along with formal indicators such as accreditation results and employment outcomes, to develop a fuller picture of performance and responsiveness improvements (Kayyali, 2024; Ntshuntshe-Matshaya, 2021). The combination of these data sources is increasingly done in dashboards and integrated analytics environments that promote the early identification of issues and a more proactive intervention (Gonçalves et al., 2023; Li et al., 2025). Likewise, the concern of the meaning of the quality standards has changed from strict conformance to manufacturing standards to more flexible alignment with global standards, quality improvement frameworks and contextual accreditation. Higher education is increasingly focusing on student needs, stakeholder satisfaction, inclusive education, innovation, and continuous improvement, rather than just the conformity of products (Hillman & Baydoun, 2019; Kayyali, 2024).

Leadership plays a role in the expansion of important methods. The plant managers were often responsible for quality improvement in industrial total quality management. However, in higher education, more distributed, strategic, ethical, and digital leadership is expected now. Increasingly academic leaders are asked to define institutional quality visions; support middle managers to test improvement initiatives in an agile fashion; and endorse digital platforms to enable continuous tracing, learning analytics, and evidence-informed decision-making (George & Wooden, 2023; Khairullah et al., 2025; Ntshuntshe-Matshaya, 2021). Concurrently, these developments are helping to address a long-standing weakness in higher education quality management, which is institutional silos. Current trends advocate the concept of a consolidated quality portfolio, whereby data sourced from learning management system, student information systems, student support services, finance units and accreditation can be merged into a common analytical framework that can facilitate cross-functional decision-making (Alotaibi, 2024; Gonçalves et al., 2023; Zabalawi et al., 2024).

Nevertheless, AI-supported quality management nevertheless entails new governance risks that classical TQM models did not take full account of. These include algorithmic bias, data privacy issues, limited explainability, cybersecurity threats, reliance on automated recommendations, and the risk of reducing quality education to narrow numbers (Oncioiu & Bularca, 2025; Popoola et al., 2024). Governance must focus on a human-centred oversight process to support the execution of institutional policies and future capacity building strategies so that AI impacts on teachers, learners and administrators rather that replaces professional judgement (Mökander & Floridi, 2023). As a result, an Adaptive AI-Driven TQM model should not only expedite PDCA, but also incorporate ethical safeguards, human oversight, transparent decision rules, and stakeholder accountability at every stage of the quality cycle.

Despite these key developments, the sustainable embedding of TQM within academic and administrative areas remains a challenge. Despite efforts to enhance quality in healthcare institutions, the transformation from isolated quality activities to full-fledged integrated quality systems is often impeded by constraints such as limited resources, cultural resistance, weak alignment of incentives, legacy systems, fragmented databases, and staff preparedness issues (Catanzano et al., 2022; Jasti et al., 2021; Tabish, 2024). Due to this, there is an increasing need for more contextual maturity models that will enable the university to step by step from disparate pilot efforts towards more coherent and institution-wide quality ecosystem (Kayyali, 2024; Setyadi et al., 2025). Table 3 presents major adaptation dimensions, which demonstrate how essential industrial TQM principles were adapted into academic ones. These adaptation dimensions apply to components: PDCA Transformation, Governance, Leadership, Culture, Stakeholder Engagement and System Integration. The quality model as re-engineered is visually represented in Figure 5 showing how iterative feedback loops, multi-stakeholder engagement, blended measurement systems and AI-supported analytics may work as a dynamic quality assurance mechanism to enhance the teaching-learning process, research and services.

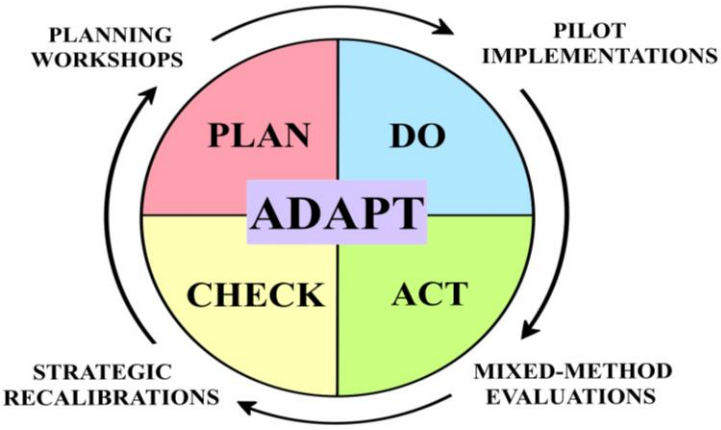


Figure 5: Academic TQM Adaptation Model

In essence, classical TQM is a valuable tool for quality improvement in higher education. However, it is also critically asserted that classical PDCA is insufficient on its own for the 2026 digital university. The linear, delayed, and audit-centric system must instead be replaced by a live adaptable AI-driven cycle that can sense, predict, intervene, oversee and engage with all stakeholders. This offers the theoretical justification for the Adaptive AI-driven Total Quality Management model proposed in this review.

Table 3: Academic TQM Adaptations

Component	Industrial Focus	Academic Adaptation	Metric Type	Stakeholder	Cycle Frequency	Anticipated Impact
PDCA Cycles	Production process improvements	Curriculum & instructional iterations	Quantitative & Qualitative	Students, Faculty	Continuous	Enhanced curricular relevance
Customer Focus	End-user satisfaction (product)	Multi-stakeholder feedback panels	Survey, Focus Groups	Students, Employers	Annual and Ad hoc	Deeper stakeholder alignment
Employee Involvement	Shop-floor teams	Cross-functional quality circles	Participation rates	Faculty, Admin staff	Quarterly	Collective ownership of quality
Measurement & Evaluation	Defect rates	Blended data: retention, satisfaction, learning analytics	Mixed methods	Quality Office	Real-time	Proactive issue detection
Quality Standards	Conformance to specifications	Accreditation & global benchmarks	Accreditation scores	Accreditation bodies	Cyclical (3-5 yrs)	Sustained compliance & innovation
Leadership Responsibility	Plant managers	Academic leaders' strategic quality vision	Dashboard KPIs	Senior leadership	Monthly	Strategic coherence & responsiveness
Strategic Planning	Production forecasts	Data-driven learning analytics forecasting	Predictive analytics	Planning office	Semestral	Anticipatory resource allocation
Continuous Feedback	Final inspection results	Iterative e-portfolios & peer reviews	Qualitative feedback	Peers, Students	Ongoing	Adaptive instructional improvements
System Integration	ERP & SPC systems	Unified quality data platforms	Data integration index	IT, Quality departments	Continuous	End-to-end visibility & agility
Governance	Management reviews	Inclusive governance councils	Governance maturity	All stakeholders	Annual	Shared accountability across institutions
Technology Use	Automation in assembly	Learning management systems & analytics dashboards	Usage analytics	Faculty, Students	Continuous	Informed teaching & learning practices
Culture Change	Quality culture training	Reflective practice & change-agent networks	Culture survey scores	All university members	Annual	Deepened quality mindset

Integration across Academic and Administrative Units

The efficiency of TQM implementation in higher education institutions depends strongly on its integration of the academic units and administrative units. As noted earlier in Section 2.2, quality in institutions is not a product of administration alone nor of teaching and research alone. Alternatively, it is produced when the curriculum delivery, student support, research management, budget, facilities, human resources and information system interact with one another. To this end, successful TQM would involve, as Harvard says, a close alignment between academic functions and the administrative operations so that institutional goals can be pursued in a coordinated way (Cheah et al., 2023). Nevertheless, the quality practices at many universities are still positioned within separate units, while the academic departments and the administrative offices have separate systems which do not interface with each other. The institutional actors' inability to communicate their ideas adequately leads to fragmentation of information, duplication of efforts and inconsistent engagement of stakeholders (Jasti et al., 2021).

Integration starts with aligning the strategies between function and business. Administrative processes that are efficient, responsive, and adequately resourced underpin academic goals such as students' success, quality curriculum, and excellence in research. Problems of budgeting, procurement, infrastructure, staffing are not merely operational problems. They should not be treated as such. Rather, they are enabling conditions of academic quality (Rahman & Nasrin, 2024). The successful integration of data to strengthen the system. Connecting learning management systems, student information systems and enterprise resource planning platforms can provide more complete visibility of enrolment trends, student satisfaction, resource use, and operational performance. The integration of various data sets allows faster, proactive decision-making at faculty and executive levels (Sawhney et al., 2019).

Controlled standardisation is also required for integration but that should not be affected by uniformity in academic practices. In the context of this review, the standardisation refers mainly to common data formats, reporting templates, communication protocols, quality indicators, dashboard structures and escalation procedures. It is important that the academic and administrative units exchange information in a consistent and comparable manner. However, there may be contingently flexible pedagogical execution, curriculum delivery, teaching, learning and student engagement processes, discipline-specific improvement measures, etc. A PDCA cycle, tailored for the university context, should offer a common quality language and facilitate coordinated flow of evidence, whilst allowing each faculty, department, and service unit to respond to its own academic context and operational needs (Hillman & Baydoun, 2019).

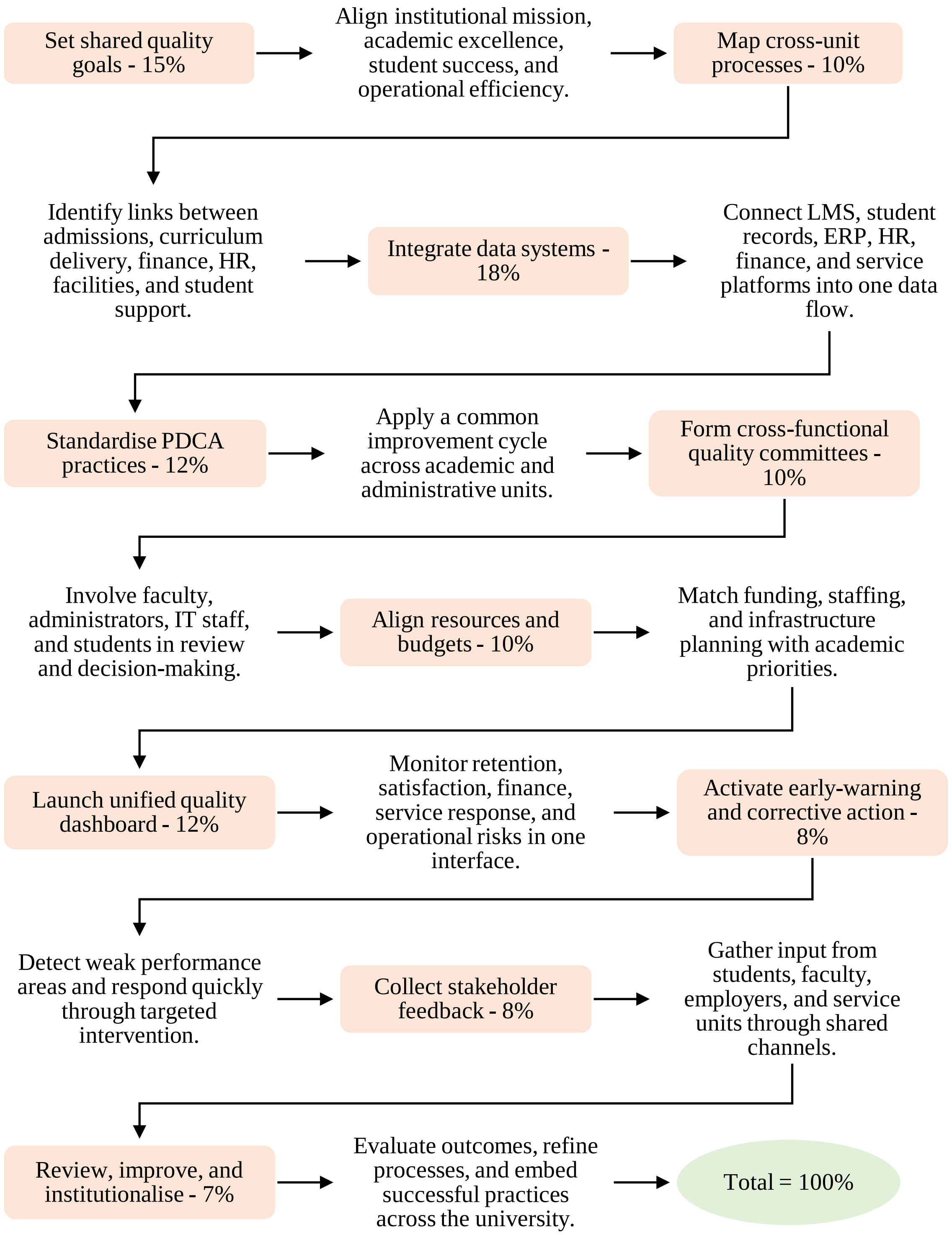
This differentiation is crucial since the weakness of classic TQM in higher education is not coordination itself, but rather improvement cycles that are overly tight such that they delay action too much and restrict local innovation. An integrated TQM systems for universities should standardise the infrastructure of quality communication, while sustaining the professional autonomy and adaptive capacity of academic units (Jasti et al., 2021). Integration, in this sense, fosters flexibility rather than constraining it. When measures and reporting are aligned, departments can compare evidence, [identify] risks and act faster, without being forced to use the same pedagogies or the same improvement interventions (Cheah et al., 2023; Zabalawi et al., 2024).

It is also important to develop stronger stakeholder engagement mechanisms, which include regular input from faculty, administrative staff and students in the design and evaluation of quality. When cross-functional quality committees are set up, review meetings, where staff have an opportunity to give and receive inputs on quality design and evaluation, and feedback loops for communicating the accomplishments and challenges at the quality committee are created, faculty members, administrative and support staff and students can get involved in quality design and evaluation (Jasti et al., 2021). According to Gamage et al. (2020), this may enhance ownership, increase collaboration, and reduce resistances to change.

Combining academic and administrative quality systems is neither easy nor simple but rather complex. It is becoming increasingly difficult to integrate owing to the same interdependence. Curriculum design improvements are unlikely to make much difference when enrolment systems fail to work well. The timely and reliable maintenance of facilities is essential to teaching innovation. It may happen as soon as resources are stretched, financial planning and pedagogical priorities may be in conflict. So, for the competing needs, good governance, and fair decision-making is a must. Therefore, integrated TQM in higher education must be underpinned not only by systems and tools, but also by governance structures able to manage interdependence, compromise priorities and establish institutional trust (Hillman & Baydoun, 2019; Kayyali, 2024).

In view of which, leading institutions increasingly began using a common interface showing key data from finance, human resources, academic and student support. Digital dashboards and integrated performance visualizations combine to facilitate cross-unit collaboration and allow corrective action to be executed faster when problems are detected (Gonçalves et al., 2023; Javed & Alenezi, 2023). Based on Hillman and Baydoun (2019) and Kayyali (2024), furthermore, external accreditation processes as well as quality assurance framework and peer benchmarking exercises have coerced institutions to provide evidences of stronger organization of their integrated quality system and academic and administrative level. Nonetheless, crucial barriers continue to exist such as disputes over data ownership, weak IT interoperability and continued silo-based mindsets. According to Alotaibi (2024) and Zabalawi et al. (2024), it is explicitly exhibited through such issues that integration entails a cultural and managerial task along with a technical one. As such, tailored change management strategies and ongoing staff development are needed to support a common institutional vision of quality (Bah et al., 2024; Catanzano et al., 2022).

To elaborate on this process, the flow between the various academic and administrative units as presented in Figure 6. The integrated TQM model for higher education in Figure 7 represents a broader view, while Table 4 shows the main integration dimensions. Collectively, these visuals depict that the assurance of the success of permanent institutional enhancement relies on coordinated processes, shared flows of information, flexibility in the academic and governance system across the university.



**Note:* These percentages are conceptual implementation weights.*

Figure 6: Cross-Unit Quality Integration Process

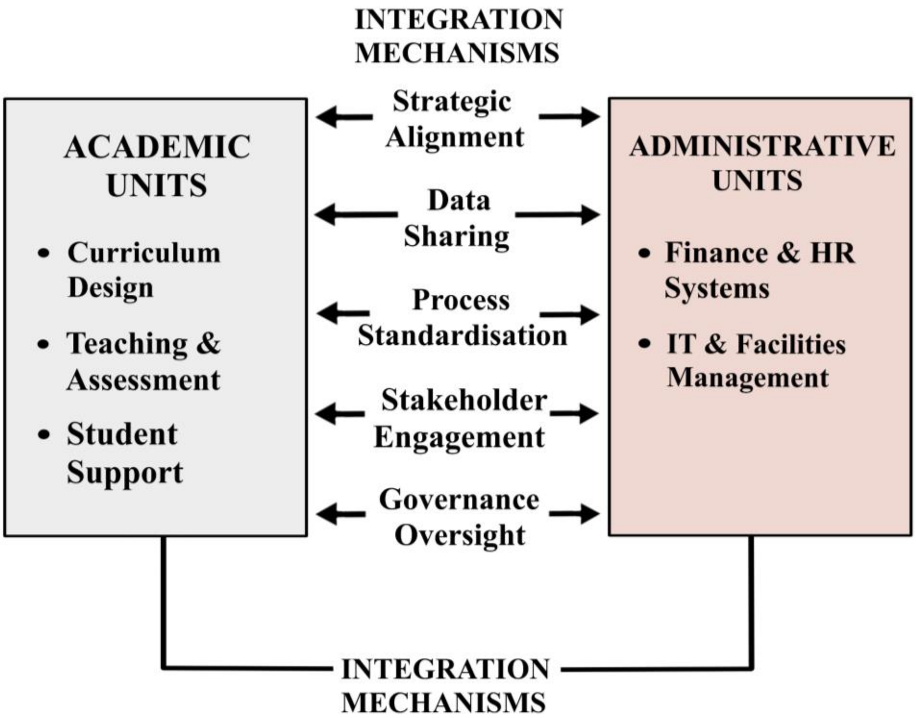


Figure 7: Integrated TQM Model For Higher Education

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Table 4: Key Integration Dimensions

Dimension	Academic Units	Administrative Units	Integration Mechanism	Benefits	Challenges	Ref.
Strategic Alignment	Curriculum design	Strategic planning	Joint planning workshops	Coherent institutional mission	Conflicting priorities	(Cheah et al., 2023)
Data Sharing	Student records	Finance & HR systems	Integrated data platforms	Real-time insights	Data ownership disputes	(Jasti et al., 2021)
Process Standardisation	Teaching & assessment cycles	Procurement & maintenance protocols	Unified PDCA frameworks	Streamlined quality assurance	Overly rigid processes	(Rahman & Nasrin, 2024)
Stakeholder Engagement	Faculty reviews	Administrative feedback channels	Cross-functional quality committees	Increased buy-in	Resistance to change	(Sawhney et al., 2019)
Enrolment	Admissions criteria	Registrar operations	Shared online application systems	Improved student onboarding	System interoperability	(Hillman & Baydoun, 2019)
Financial Management	Department budgets	Central finance	Joint budget allocation processes	Transparent resource use	Competing budget demands	(Gamage et al., 2020)
Facility Maintenance	Classroom scheduling	Building services	Real-time maintenance tracking	Reduced downtime	Reactive rather than proactive	(Gupta et al., 2023)
Human Resources	Faculty recruitment	Staff administration	Common recruitment platforms	Holistic talent management	Role ambiguity	(Al-Dhaafri & Alosani, 2020)
QMS Coordination	Academic quality offices	Quality assurance units	Central quality management office	Consistent quality policies	Duplication of effort	(Javed & Alenezi, 2023)
Risk Management	Academic risk assessments	Compliance and audit divisions	Integrated risk registers	Comprehensive risk oversight	Varying risk appetites	(Xu et al., 2022)
Feedback Loops	Student course evaluations	Service satisfaction surveys	Shared feedback portals	Holistic improvement inputs	Survey fatigue	(Sawhney et al., 2019)
Compliance & Accreditation	Program accreditation documentation	Regulatory reporting	Unified compliance dashboards	Streamlined accreditation readiness	Complex regulatory frameworks	(Xu et al., 2022)

Common Shortcomings

According to studies conducted by Hillman and Baydoun (2019), Gamage et al. (2020), and Sawhney et al. (2019), TQM implementation does not have the intended impact in universities as in reality quality problems are interrelated rather than isolated. In higher education systems, the improvement processes are often hindered by the fragmented nature of data systems, rigid quality cycles, limited participation of stakeholders, outdated performance indicators, weak technological integration, resistance to change, skills gaps, limited resources, accountability gaps, change fatigue, measurement delays and the leadership-by-silo approach. These inadequacies limit universities' ability to transition from formal quality assurance to continuous, evidence-based and student-centred improvement.

Data silos continue to be one of the greatest problems in most enterprises. According to a study by Gamage et al. (2020), academic data, student-support systems data, and administrative data are kept in distinct platforms, that is learning management systems, student information systems, enterprise resource planning systems, and accreditation databases. Decision-makers get incomplete and slow information when these systems are not joined. Universities may identify student disengagement with services, specific delays in service delivery, or quality issues at the programme level too late. The aim of TQM is to facilitate the timely, systematic, and evidence-based improvement.

Another large disadvantage is the rigid application of the PDCA cycle. According to Aggarwal (2020), the universities apply a fixed sequence with the PDCA cycle which is usually annually planned, delayed review and end-of-cycle correction. As a result, it becomes too procedural. In such situations, the cycle may facilitate accordance reporting. By contrast, it does not always facilitate rapid intervention. Supply a great essay on higher education. One of the challenges to higher education is people's belief that they know how to learn. The issue lies not in the PDCA logic, but in its implementation, which is slow and retrospective There is a requirement for a more adaptable PDCA where, on the side, they can monitor data and adjust improvement actions during the semester and not after.

Exclusion of stakeholders is another major barrier. Sawhney et al. (2019) stated that quality initiatives have reduced efficacy when students, teachers, admin staff, employer and alumni are not engaged meaningfully in the improvement process. In many universities, quality decisions are still mainly made by top-down committees or formal reporting lines. Ownership may be reduced, trust may be damaged, and resistance to change may be generated. High quality of higher education entails the involvement of different actors; hence, stakeholder engagement should not be treated as a mere symbolic requirement, but more importantly, as a key mechanism to identify problems, design solutions and assess outcomes of the improvement effort.

Another limitation is narrowly defined and static Key Performance Indicators (KPIs). Hillman and Baydoun (2019) observed that universities rely substantially on traditional indicators like graduation rates, employment rates, accreditation outcomes, and student satisfaction evaluations. These indicators – though useful for reporting and benchmarking purposes – offer incomplete and lagged information on institutional performance. For example, graduation rate is an important outcome measure, but it does not tell us why students disengage, when the risk from school begins, how students experience teaching quality, and whether administrative services respond adequately. Accordingly, conventional KPIs usually come too late, are too imprecise, and focus on outcomes rather than on processes.

The TQM system powered by AI of tomorrow must go beyond the traditional KPIs and consider dynamic, predictive, and diagnostic indicators. For instance, such KPIs can mean real-time sentiment analysis of LMS discussion forums, automated complaint classification, early-risk score for student dropout, response-time of student service requests, course engagement heatmaps, attendance-risk prediction, online lesson participation trend, real-time feedback/satisfaction signal from chatbots or feedback loops, among others. AI-powered style guide, which is an eclectic mix of colour, design patterns, word font and combinations and so on, serves as a critical tool to streamline edits of all editions, especially digital. So, the quality measurement transforms responsiveness reporting into action reporting.

TQM effectiveness is also limited by technology fragmentation. Al-Dhaafri and Alosani (2020) discovered that a lack of communication between digital systems leads to limited development of a unified view of institutional quality in universities. Data on a student's academic performance may be in one system, their complaints in another, finance data in a third system, and staff workload data in yet another. The fragmentation prevents leaders to understand how academic and administrative factors interact. Additionally, using AI tools is also becoming a challenge as predictive models need clean, connected, and reliable data.

Another significant challenge is cultural resistance. According to findings from Didham and Ofei-Manu (2020), it has been identified that employees resist the quality initiatives when they view them as extra administrative burden, external controlling devices and a threat to professional autonomy. Resistance to change intensifies when digital tools and AI systems are implemented without proper explanation, training, or ethical safeguards. Thus, it is essential that universities develop a quality culture which, in addition to compliance, is based on trust, participation, transparency, and shares responsibility.

The implementation of TQM is affected by skills gaps. According to Jasti et al. (2021), staff and managers often lack the digital, analytical and quality-management skills required to effectively use the tools available. Even when universities invest in dashboards, analytics systems, or AI-supported platforms, these tools may not be fully used if staff cannot interpret the information and use them for improvement. Therefore, through modern TQM in higher education, staff development, data literacy and AI literacy become the essential conditions.

Inadequate resources further restrict the sustainability of quality improvement. Tabish (2024) discovered that several universities face financial, staffing, and infrastructure constraints that compel them to give priority to basic compliance instead of deeper improvement. When quality offices lack sufficient resources, they may only focus on documentation, accreditation files, and period reports, rather than continuous improvements. This diminishes TQM's transformative power, fostering a culture of just meeting the minimum.

Implementation is also weakened by accountability gaps. Quality initiatives may fail if assignments are not made clear through the various departments, faculties and administrative units (Chigbu & Makapela, 2025). If it is not obvious who is responsible for doing something about quality data, then problems will remain unresolved. In AI driven quality system predictive alerts, and signals on dashboards should be coupled with the decision-maker, protocol for responding, and follow-up action.

The first of these is change fatigue. The staff may experience fatigue, cynicism or disengagement as a result of continual reforms, new reporting requirements, technology changes and accreditation pressures (Gardezi, 2024). When an institution perceives correction as a form of continuous evaluation, the staff may appear to comply but resist practice. This undermines TQM's long-term embedding.

Measurement lag also comes with a serious limitation. Quality systems in traditional setup can be annual surveys, course evaluations at the end of every semester, periodic audits, delayed performance reports, etc. Although these are good tools, most of the time they will give you information once the opportunity to intervene has passed. Using AI analysis on live or near real-time data such as student feedback, helpdesk tickets, attendance patterns, assessment submissions, and online engagement may help in fixing this lag. This enables universities to pick out any early warning signs and to take corrective action before issues become final performance outcomes.

Considering all these limitations, it demonstrates that enhanced TQM in higher education must not be improved in isolation. According to Hillman and Baydoun (2019), holistic business architectures are needed by universities to embed the quality assurance approach into a flexible cycle that relies on integrated data systems. According to this review, the prime implication is classical TQM need a strengthening through AI-enabled mechanisms fortifying real-time monitoring, predictive analysis, automated feedback and adaptive intervention. Table 5 summarizes the main shortcomings just mentioned.

Table 5: Common TQM Barriers

Study	Barrier	Description	Impact	Underlying Cause	Proposed Solution
Gamage et al. (2020)	Data Silos	Disconnected ERPs, LMSs	Delayed decisions, inefficiency	Platform incompatibility	Unified data architecture
Aggarwal (2020)	Rigid PDCA Cycles	Linear, retrospective cycles	Reactive interventions	Inflexible process design	Agile PDCA with embedded analytics
Sawhney et al. (2019)	Stakeholder Exclusion	Marginalised faculty and support services	Low buy-in, reduced effectiveness	Top-down governance	Cross-functional quality teams
Hillman and Baydoun (2019)	Static KPIs	Fixed, lagging indicators	Misaligned objectives	Metrics inertia	Balanced scorecards with leading indicators
Al-Dhaafri and Alosani (2020)	Technology Fragmentation	Multiple siloed systems	Blocks AI integration	Poor interoperability	Integrated digital ecosystem
Didham and Ofei-Manu (2020)	Cultural Resistance	Hesitancy to adopt new practices	Slow adoption	Fear of change	Comprehensive change management
Jasti et al. (2021)	Skills Gap	Insufficient analytics expertise	Underutilisation of tools	Lack of training	Ongoing professional development
Tabish (2024)	Resource Constraints	Limited budget and staff	Prioritisation of compliance	Financial limitations	Strategic resource allocation
Chigbu and Makapela (2025)	Accountability Gaps	Unclear roles and responsibilities	Initiative failures	Weak governance	Defined accountability frameworks
Gardezi (2024)	Change Fatigue	Overloaded staff and competing projects	Burnout, loss of momentum	Excessive project load	Phased, prioritised improvement roadmap
	Measurement Lags	Manual data collection and reporting	Slow insight generation	Antiquated processes	Automated real-time dashboards
Tabish (2024)	Siloed Leadership	Departmental agendas, fragmented vision	Fragmented strategy	Decentralized leadership	Institution-wide leadership councils

AI-Driven Technologies and Integration Challenges

Mariam et al. (2024) describe that due to the increasing complexity of institutions of higher education, universities are increasingly applying machine learning (ML) and predictive analytics for research-based decision-making in academic and administrative areas. To reduce reliance on historic reports that aren't always timely, institutions can make use of current and predictive data to spot trends and potential risks, enabling earlier student 7support. The use of ML methods as part of an AI-enabled TQM system should not be seen merely as technical tools. They should be directly linked to key TQM pillars like stakeholder focus, continuous improvement, factual decision-making, process management and leadership commitment. These pillars are supported by different ML methods.

- Decision trees help focus on stakeholders and fact-based decisions part of total quality management as these classify students or service users into interpretable risk groups. They may find students in need of academic advising, financial assistance, learning assistance or other help based on attendance, LMS activity, assessment performance and service interaction data.
- Random forests support the TQM pillar of process management because they improve prediction accuracy by combining multiple decision paths. As a result, universities can monitor a complex process of academic and administrative more authentically and minimise the risk of a weak decision based on a single predictive model.

- Neural networks support the TQM pillar of continuous improvement because they can model complex non-linear relationships, such as student engagement, assessment behaviour, learning resources, and final grades. The findings of Ezzaim et al. (2024) can help the universities improve curriculum design, learning support and resource allocation.
- LSTM networks which are long short-term memory networks supports the TQM pillar of fact-based decision making as they analyse time-series data and can detect changes in student progression over time. Malashin et al. (2024) state that LSTM models can predict the risk of dropout and identify early signs of a student's poor performance allowing for timely preventive action against student failure.

Nonetheless, the usefulness of these models hinges heavily on the quality of the underlying data. As per Aldoseri et al. (2023) and Elouataoui et al. (2023), predictive performance may be diminished and institution-based trust in AI-produced results may be weakened due to incomplete records, inconsistent entries, duplicated data, and delayed updates. Therefore, robust data governance frameworks and automated ETL pipelines can help ensure that data is accurate, timely, standardised, and usable. Furthermore, Gonçalves et al. (2023) assert that the use of real-time data capture and visualisation platforms, including Tableau and Power BI as well as dashboards created for specific institutions, facilitates the better use of more complex outputs generated through machine learning in management.

To allow successful A-I TQM integration, a clear technical architecture is required by universities. The architecture must not depend on a generic "middleware" but must include API-led connectivity, a common data model (CDM) for higher education, automated ETL/ELT pipelines, standard student and course identifiers, data quality rules, metadata governance and role-based dashboard access. API enable learning platforms (LMS), student information systems (SIS), and other enterprise systems (ERP) like finance, HR, library, student support, and accreditation to exchange data in almost real time. A higher education CDM ensures consistency in the definitions of key terms such as student status, course enrolment, attendance, progression, withdrawal, complaint, service request, and learning outcome across units. An adaptive TQM cycle requires the equivalent and reliable evidence since Plan, Do, Check and Act stages all depend on it.

The LMS is used to deliver online courses, and it is a virtual equivalent of a classroom that allows students to log in to complete assignments and materials. At the Plan stage, leaders can leverage integrated data to pinpoint key risks and establish improvement goals. During the Do phase, systems linked via APIs can initiate actions like advising, service follow-ups, and curriculum support. The Check stage will use dashboards to monitor if interventions improve student engagement, satisfaction, retention, or service response time. In the Act stage, institutional leaders can rebuild policies, workflows, or mechanisms for teaching support based on generated evidence. Figure 8 illustrates this flow in terms of the collection and preprocessing of raw data, followed by predictive modelling and a dashboard visualisation.

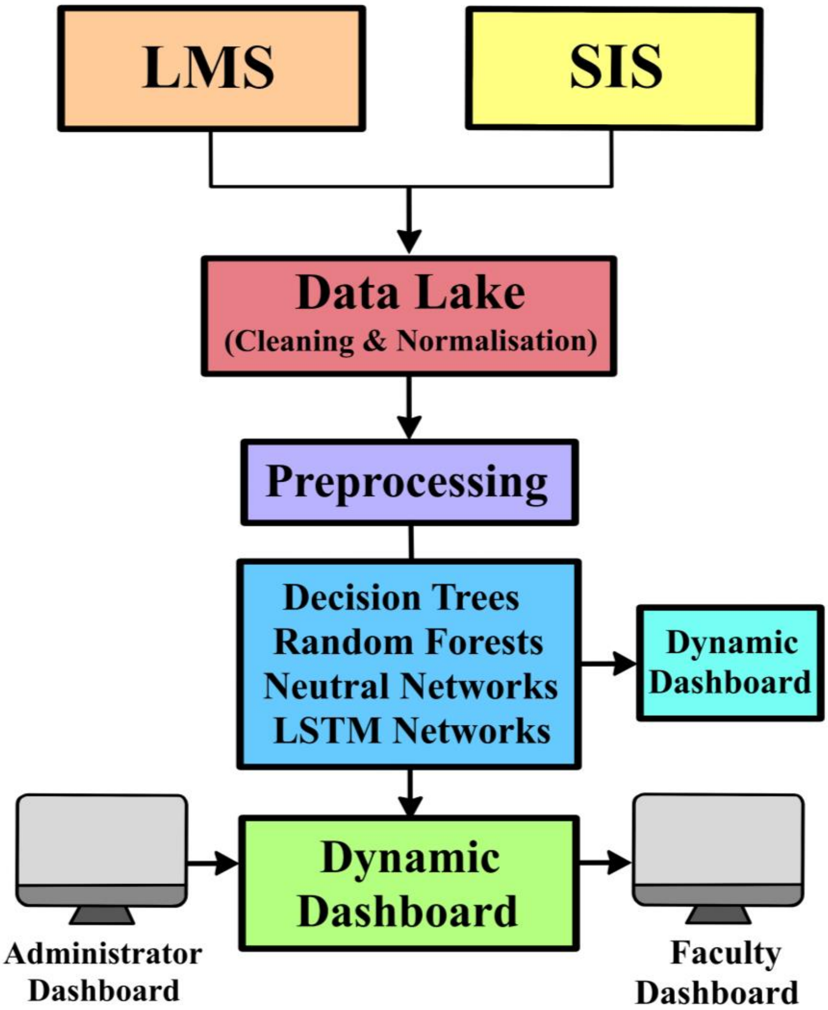

Figure 8: The ML Analytics Integration Model

While there have been positive advancements, there are still several technical barriers that stand in the way of full use of AI in higher education. Interoperability is among the most persistent challenges as per Kadri et al. (2022) and Yusuf (2023). Numerous universities continue to operate with legacy platforms where SIS, LMS, ERP, finance, and HR systems do not share a common data model, standard API, or shared governance rules. Due to this, federated analytics gets difficult, and dashboards may show partial, delayed, or inconsistent data. In contrast to the promise of real-time oversight, this fragmentation which exists can lock institutions into reactive management cycles. In the same way, Acharya et al. (2025) established that the benefit of early-warning systems may be effective only when there is strong integration of APIs, automation of ETL processes, setting up of data validation rules and systematic synchronisation.

When alerts are still being manually reported or delayed, they have little predictive value. Apart from technical matters, significant organisational barriers also persist. A significant limitation, as Catanzano et al. (2022) as well as Jasti et al. (2021) point out, is a low level analytics literacy on the part of many faculty and administrators. Even with the availability of digital tools, the institutional significance of the outputs might remain relatively limited if the intended users do not possess the requisite confidence or competency to interpret or act on them. Correspondingly, Anastasiou and Ntokas (2024) state that it is not only lower-income economies, but also cultural resistance, especially in environments where traditional governance is strong, where automated recommendations are likely to be viewed with suspicion.

In post-secondary institutions cultural resistance is considerably more sophisticated than in the TQM of industry. This is because it is closely linked to the tension between algorithmic authority and academic freedom. In orders to make the control possible it is accepted in manufacturing stipulations that automated recommendations and standardised processes will do the trick. At universities, though, academic-staff members may see recommendations generated by AI as a threat to their professional judgement, disciplinary autonomy, pedagogical creativity, and interpretation of student learning. For example, a model may label a student "at risk", but lecturers may counter that the model does not adequately consider contextual factors such as motivation, language background, personal circumstances, or discipline-specific learning patterns. AI must not be seen as a substitute for educational expertise. Rather, it should be positioned as a decision-support mechanism which informs but does not dictate academic and administrative action.

The difference is critical for AI-enabled TQM to sustain trust. In the event that lecturers suspect that algorithm-derived conclusions will be employed in monitoring, controlling colleague performance, or mechanized judgement, then resistance will heighten. Yet, AI systems can support professional autonomy instead of undermining it when they are transparent, explainable, governed by ethical principles and aligned to academia. The real-time dashboard model (see Figure 9) represents these interactions between the technical system, user interpretation layers, academic judgement and decision layers.

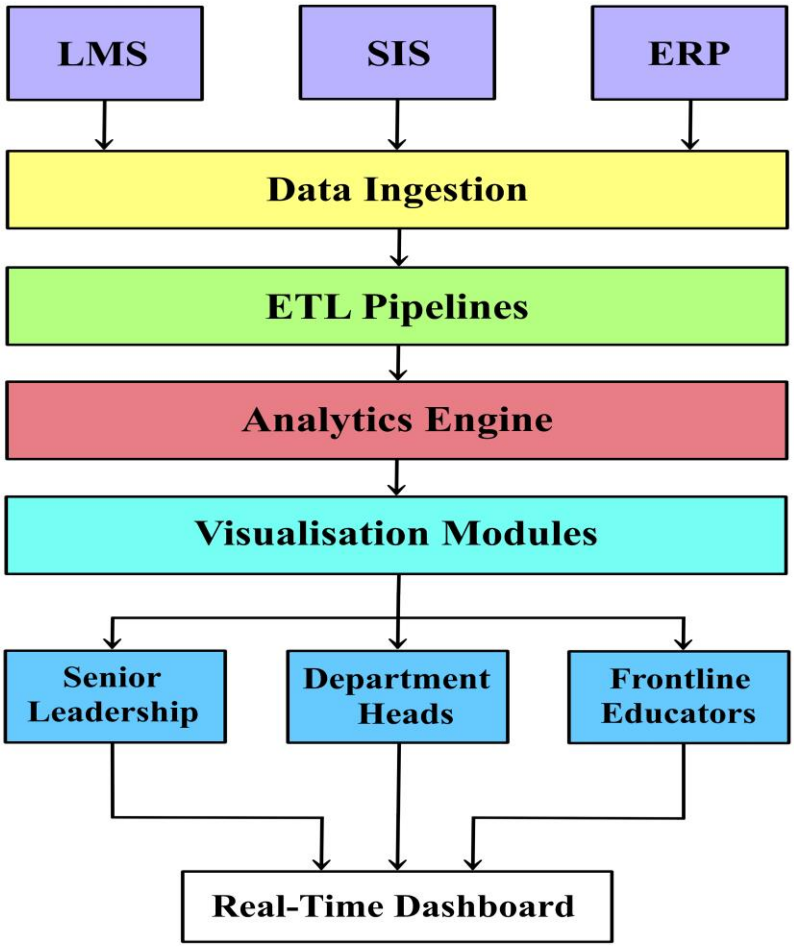

Figure 9: The Real-Time Dashboard Model

In response to these challenges, a broader institutional approach is needed. According to Catanzano et al. (2022) and Tabish (2024) sustained professional development is essential if universities want to strengthen analytics capability among academic and administrative staff. In addition, according to Acharya et al. (2025), and Anastasiou and Ntokas (2024) stronger trust in AI-supported quality systems depends on visible leadership support, transparent governance, clear ethical guidelines, and inclusive stakeholder participation. Therefore, the successful integration of AI into quality management should not be understood only as a technical project. It should be approached as an institutional transformation that requires aligned infrastructure, skilled users, supportive leadership, and a culture that is open to innovation. This broader interaction between leadership commitment, staff capability, cultural readiness, and technical infrastructure is illustrated in Figure 10.

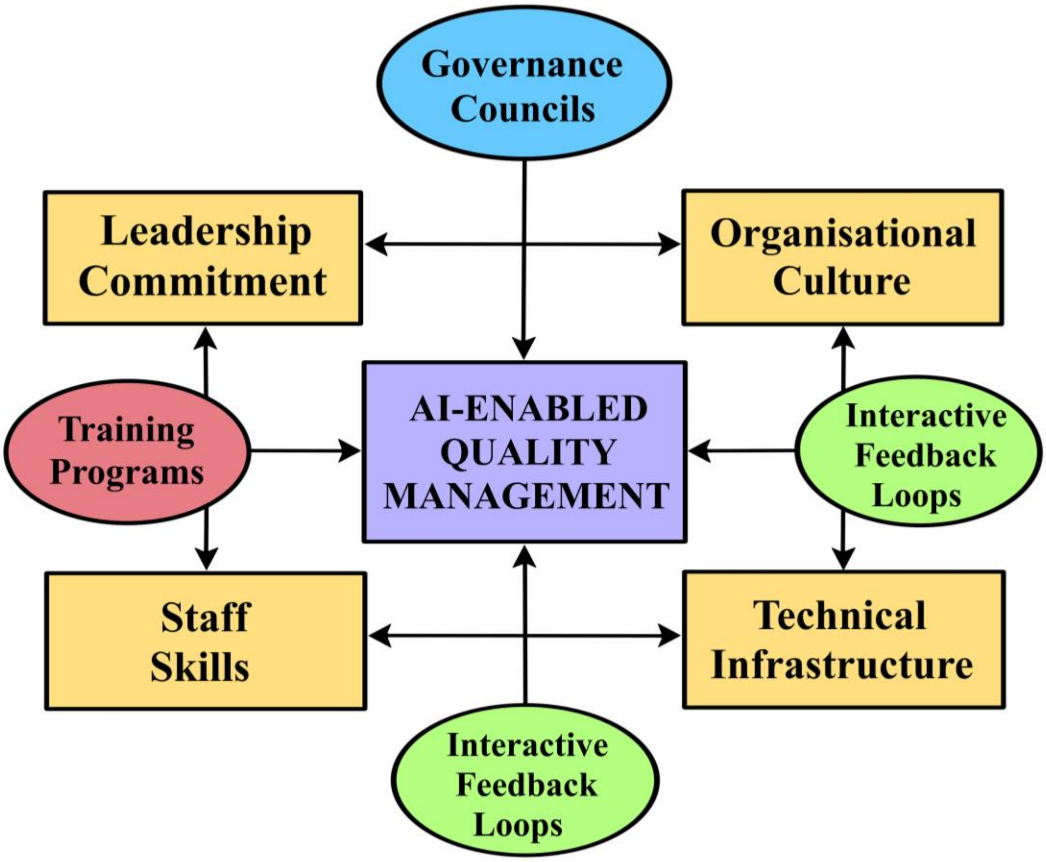

Figure 10: The Organisational Factors Model

To support this discussion, Table 6 summarises the key components of AI-TQM integration, including major ML algorithms, visualisation platforms, technical barriers, and organisational barriers. It also shows their main applications, institutional benefits, typical challenges, and mitigation strategies. Together, these elements provide a clearer roadmap for universities seeking to build more responsive, integrated, and AI-enabled quality management systems that can strengthen student success and institutional performance.

Table 6: AI-TQM Integration Components

Component	Category	Application	Institutional Benefit	Common Challenge	Mitigation Strategy	Ref.
Decision Trees	Algorithm	Classify at-risk student segments based on engagement data	Enables early, interpretable interventions	Prone to overfitting	Use pruning and ensemble methods	(Mariam et al., 2024)
Random Forests	Algorithm	Aggregate multiple tree models for performance prediction	Improves prediction accuracy and robustness	High computational cost	Parallel processing, feature reduction	
Neural Networks	Algorithm	Model complex relationships (e.g., course engagement vs. grades)	Delivers high-precision trend analysis	Low transparency (black box)	Apply SHAP/LIME explainability tools	(Ezzaim et al., 2024)
LSTM Networks	Algorithm	Forecast retention and progression using sequential data	Real-time alerts for emerging at-risk patterns	Requires large, clean time-series datasets	Transfer learning, data augmentation	(Malashin et al., 2024)
Tableau	Visualisation	Interactive dashboards pulling LMS, SIS, and ERP data	User-friendly insights; broad stakeholder access	Licensing costs, integration complexity	Evaluate open-source alternatives; ROI study	(Gonçalves et al., 2023)
Power BI	Visualisation	Cross-platform analytics for retention and engagement metrics	Rapid deployment, built-in connectors	Vendor lock-in risks	Standardise APIs; ensure multi-vendor skill	(Gonçalves et al., 2023)
Custom Dashboards	Visualisation	Institution-specific KPI tracking across units	Tailored decision support; brand alignment	High development/maintenance overhead	Agile development; stakeholder co-design	(Li et al., 2025)
Data Quality	Tech Barrier	Accuracy, completeness & timeliness of student/ops data	Reliable analytics; stakeholder trust	Fragmented sources; manual data entry	Automated ETL, data stewardship programs	(Girón et al., 2023)
Interoperability	Tech Barrier	Seamless data exchange among SIS, LMS, and ERP systems	Unified analytics ecosystem	Legacy/proprietary formats	Middleware, standardised data schemas	(Yusuf, 2023)
Real-Time Data Access	Tech Barrier	Immediate availability of current data for dashboards	Proactive interventions; reduced lag times	Reporting lags, siloed update cycles	Streaming APIs, event-driven pipelines	(Aldoseri et al., 2023; Elouataoui et al., 2023)
Skills Gap	Org Barrier	Analytics literacy among faculty & administrators	Maximised tool utilisation; informed decisions	Limited training; competing priorities	Ongoing professional development; credentials	(Jasti et al., 2021)
Cultural Resistance	Org Barrier	Hesitancy to adopt AI/ML-driven processes	Sustained adoption; stronger buy-in	Fear of change, distrust of automated outputs	Change management: transparent communication	(Anastasiou & Ntokas, 2024)

The Adaptive AI-Driven TQM Cycle

According to Akter et al. (2023) and Dhal & Kar (2025) the growing maturity of real-time analytics, predictive modelling, and automated decision support has made it possible to rethink quality management in higher education more fundamentally. In response to the limitations of traditional quality systems, the proposed adaptive Ai-driven TQM cycle is designed as a re-worked version of the classical PDCA framework, as mentioned in Figure 4, where real-time data, predictive AI models, and automated intervention loops are embedded across all stages of the cycle. In this model, quality management is no longer treated as a static and retrospective activity. Instead, it is reframed as a continuously adaptive system that can learn from incoming data, detect risk early, and support faster institutional response.

In the proposed model, data from multiple institutional sources, including student information systems, learning management systems, administrative workflows, and external stakeholder feedback, are brought together into a unified analytics environment. Within this environment, AI models such as neural networks, random forests, and LSTM networks are used to identify patterns, forecast risks, and trigger context-specific responses (Akter et al., 2023; Dhal & Kar, 2025). According to Tian et al. (2025) and Yusuf (2023) during the Plan phase, forecasting tools can be used to analyse historical performance and current operational conditions in order to support goal setting, resource planning, and early risk identification. In the Do phase, according to Girón et al. (2023) and Setyadi et al. (2025) real-time dashboards and live performance streams can be used to monitor intervention quality, such as curriculum pilots or student support actions, and adjust delivery through shorter feedback loops. In the Check phase, anomaly-detection tools such as Isolation Forests and random forests can identify unexpected deviations in academic or administrative performance and support rapid root-cause analysis, while forecasting models estimate future outcomes related to retention, compliance, and service efficiency (The Role of AI in Transforming Strategic Planning Processes, 2024). Finally, in the Act phase, according to Lim et al. (2020) automated intervention loops can translate insights into system-supported actions, such as targeted student alerts, dynamic reallocation of resources, or stakeholder notifications, while the results of these actions are fed back into the system to improve later decisions.

Before introducing the full architecture, the staged development of the proposed model should also be made clear. For this reason, Figure 11 is introduced before Figure 12 to show the main implementation steps through which the Adaptive AI-Driven TQM Cycle can be developed inside a higher education institution. This process begins with strategic alignment, moves through data integration and model selection, and then continues toward dashboard deployment, pilot testing, governance design, and continuous optimisation.

The broader architecture of this model is illustrated in Figure 12, where the integration of data, AI engines, and adaptive PDCA functions is shown as one continuous quality system. In this architecture, institutional silos are reduced because data is shared across units and KPIs are aligned around common quality priorities. According to Alméstar et al. (2025) this kind of integration is important because it allows institutions to respond more quickly as student needs, teaching priorities, and regulatory requirements continue to change. In this way, the proposed model does not simply add AI tools to TQM. Rather, it changes the operational logic of TQM itself by embedding adaptability into the quality cycle. To illustrate the practical depth of this integration. Table 7 maps representative examples of how AI analytics can be embedded into each PDCA phase. These examples show the application area, data source, analytics technique, intervention mechanism, feedback loop, and institutional benefit. Together, they demonstrate that meaningful responsiveness requires not only predictive models, but also clear intervention pathways and continuous feedback structures.

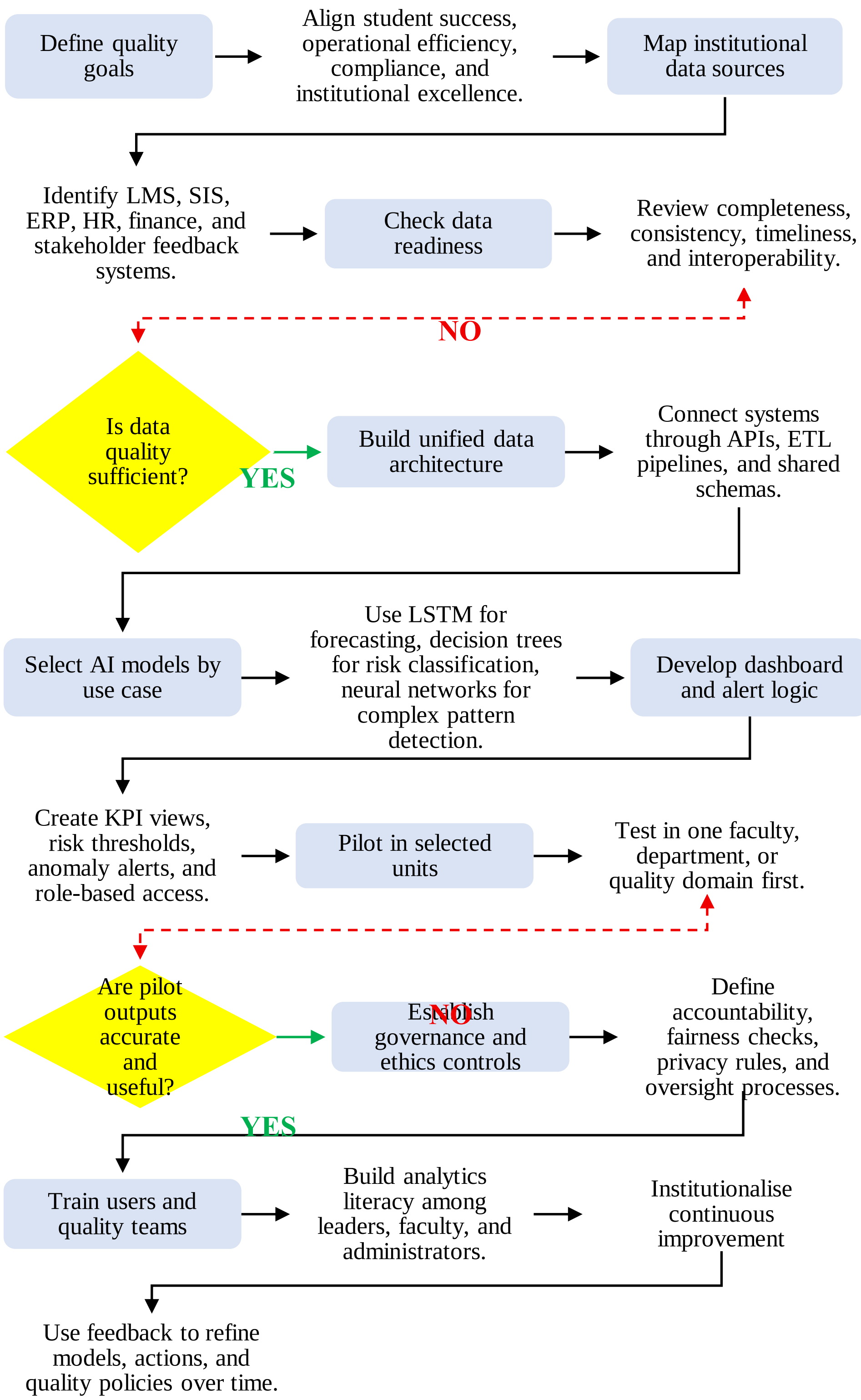

Figure 11: Development and Implementation Steps of the Adaptive AI-Driven TQM Cycle

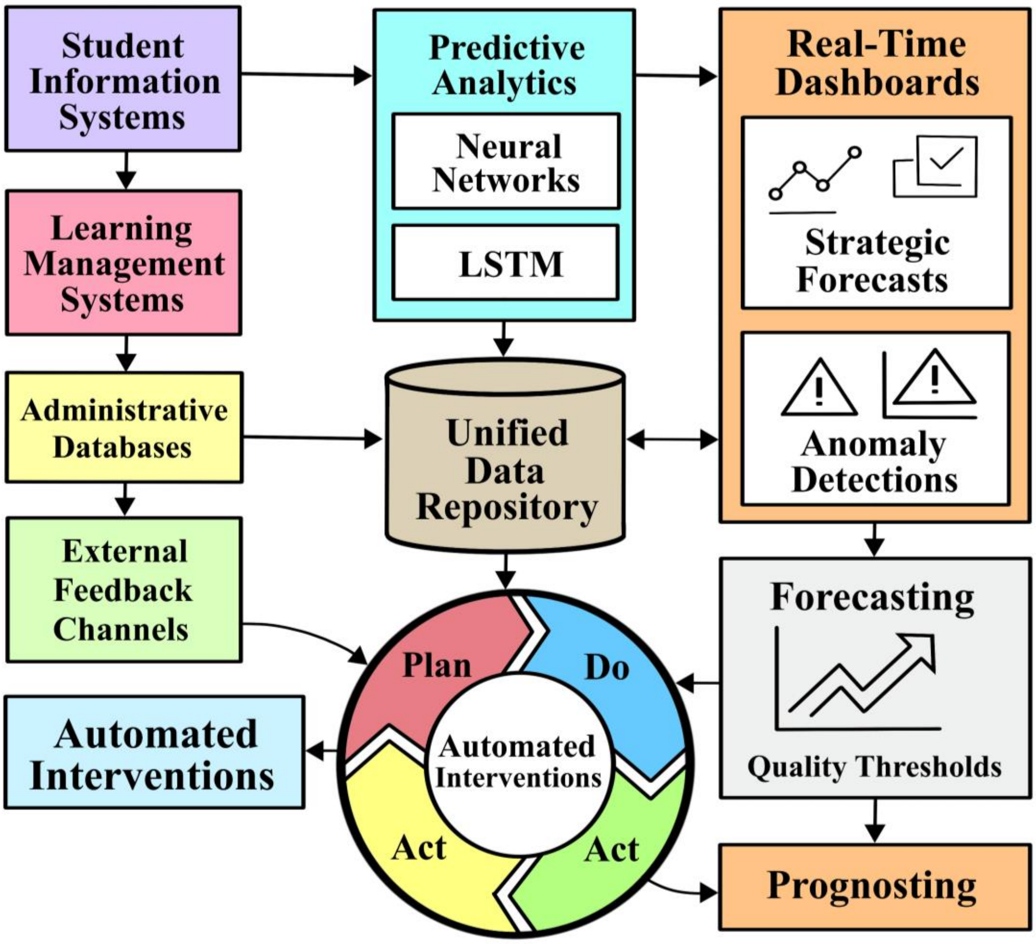

Figure 12: Adaptive TQM Architecture

Table 7: Adaptive Analytics Integration

Phase	Application Area	Data Source	Analytics Technique	Intervention Mechanism	Feedback Loop	Institutional Benefit
Plan	Strategic Forecasting	Historical enrolment & outcomes	Time-series LSTM	Scenario planning dashboards	Forecast accuracy refinement	Proactive goal alignment
Plan	Resource Allocation	Budget & staffing records	Regression analysis	Dynamic budgeting recommendations	Budget vs. actual variance updates	Optimised resource utilisation
Plan	Risk Identification	Early warning indicators	Decision tree classifiers	Pre-emptive risk mitigation alerts	Risk outcome comparison	Reduced compliance and accreditation risks
Do	Curriculum Monitoring	LMS engagement metrics	Neural network classifiers	Real-time content adjustment prompts	Engagement trend recalibration	Enhanced student learning experience
Do	Intervention Effectiveness	Intervention logs	A/B testing analytics	Adaptive intervention workflows	Comparative effectiveness reporting	Improved intervention ROI
Do	Resource Optimisation	Facility usage & scheduling	Clustering algorithms	Automated room and resource booking	Usage efficiency feedback	Cost savings and utilisation boosts
Check	Anomaly Detection	Student performance streams	Isolation Forests	Immediate deviation notifications	Anomaly threshold tuning	Rapid issue identification
Check	Predictive Forecasting	Combined academic & admin data	Ensemble forecasting	Pre-emptive support triggers	Forecast vs. actual adjustments	Early intervention in student retention
Check	Compliance Monitoring	Accreditation audit results	Rule-based AI	Automated compliance reminders	Audit outcome feedback	Continuous accreditation readiness
Act	Academic Support Alerts	Detected at-risk student data	Rule-based triggers	Personalised support notifications	Support efficacy feedback	Increased retention and success rates
Act	Resource Reallocation	Operational bottleneck alerts	Optimisation algorithms	Automated resource redistribution	Bottleneck resolution monitoring	Enhanced operational efficiency
Act	Stakeholder Notifications	Quality metric deviations	Event-driven notifications	System-driven email/SMS alerts	Notification response analysis	Improved stakeholder engagement

According to Alméstar et al. (2025) the main strength of this integrated model lies in its ability to move institutions away from being data-rich but insight-poor. By connecting predictive foresight with automated action, the proposed cycle supports a more agile and student-centred form of quality management. This end-to-end flow of data, analytics, and action is presented in Figure 13, which shows how each PDCA stage connects to the next through adaptive loops and AI-enabled transitions.

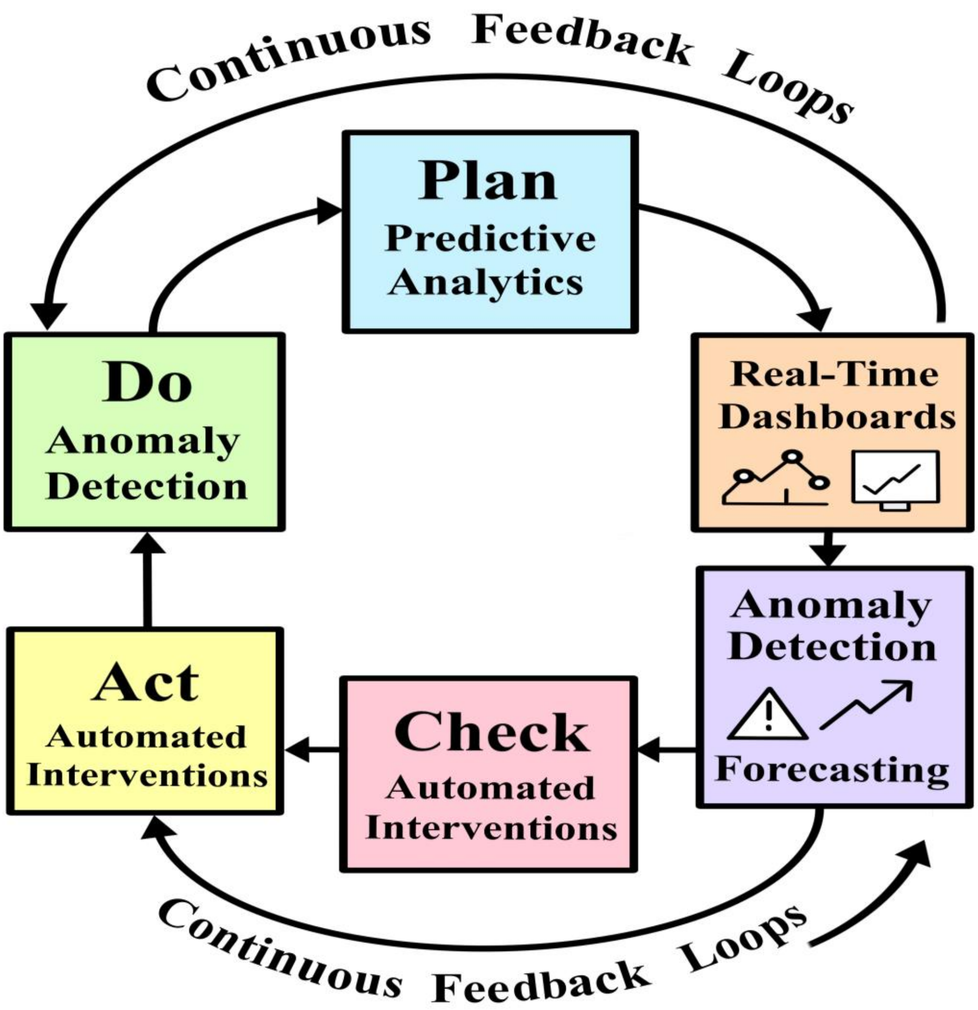

Figure 13: Comprehensive Adaptive Cycle

However, for the model to be useful in practice, institutions also need an operational protocol that explains how the proposed cycle can be used step by step after deployment. For this reason, Figure 14 is introduced after Figure 15 to present the practical use protocol of the proposed cycle. This figure is intended as a user-oriented process map that shows how universities can monitor data, assess risk, validate findings, trigger intervention, and review outcomes in an organised sequence. The proposed protocol translates the model into a practical operational protocol that institutions can follow in real settings. In this way, the proposed adaptive AI-driven TQM cycle is positioned not only as a conceptual improvement to classical TQM, but also as a practical roadmap for universities seeking to build more responsive, data-informed, and ethically governed quality systems.

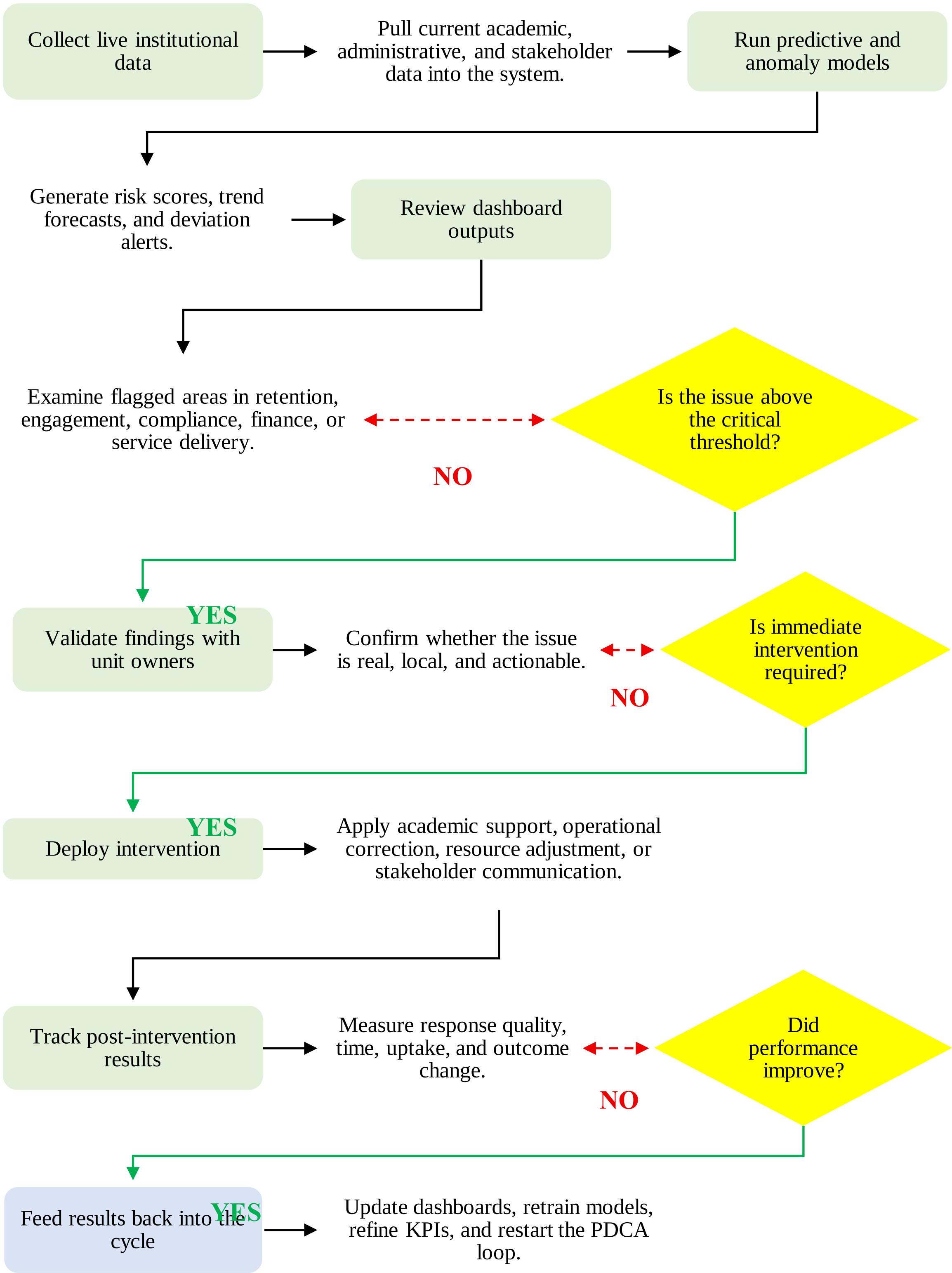

Figure 14: Operational Protocol for Applying the Adaptive AI-Driven TQM Cycle

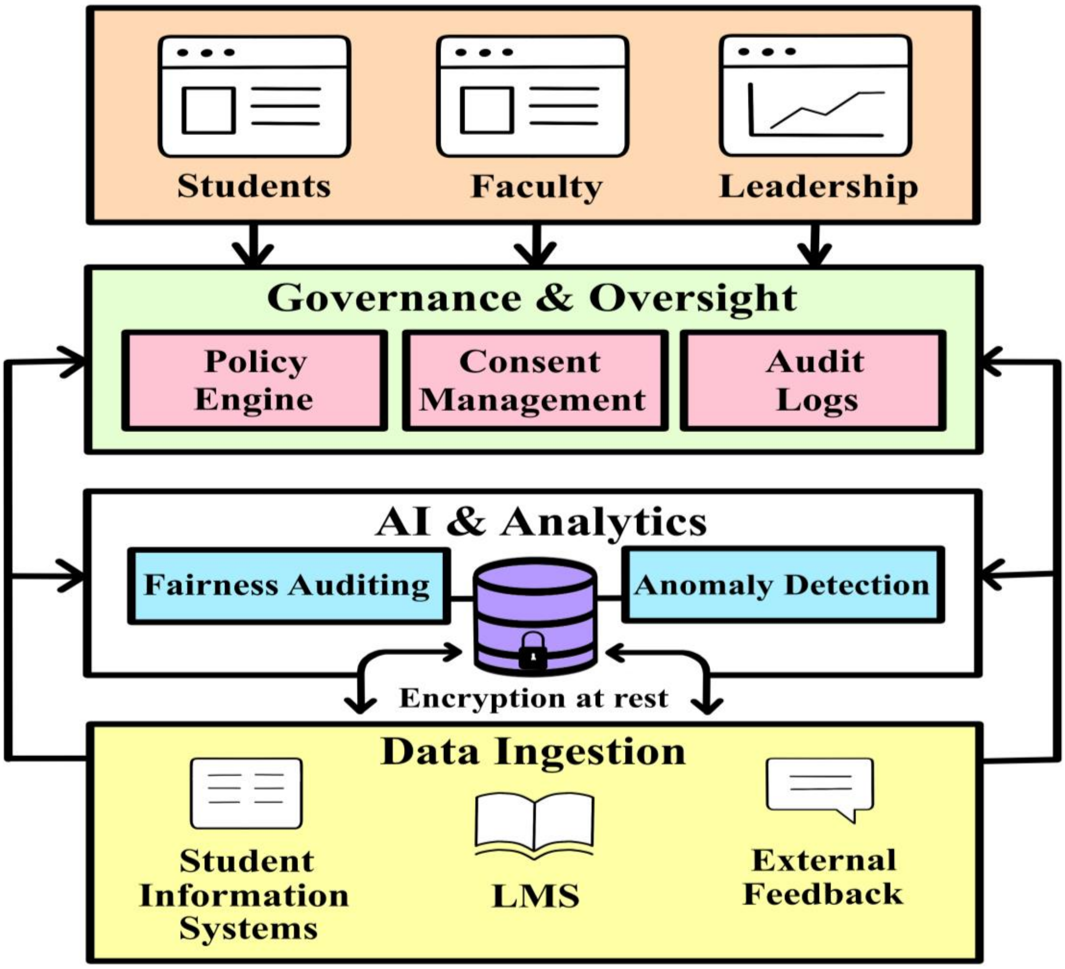

Figure 15: Data Governance Model

Ethical Considerations and Governance Frameworks

According to Oncioiu and Bularca (2025) it is not only a technical or managerial issue. This also requires well-designed systemic governance and monitoring structures for institutional credibility, stakeholder protection and ethical appropriateness. It is significant to note that educational institutions manage a large quantum of sensitive data. This may include academic records, demographic information, behavioural data, about learning engagement, and sometimes even biometric data. Thus, the deployment of artificial intelligence (AI) in quality management needs to be buttressed by strong compliance with privacy and security regulations such as the General Data Protection Regulation (GDPR) and the Family Educational Rights and Privacy Act (FERPA), alongside context-sensitive consent procedures that foster transparency and trust (Oncioiu & Bularca, 2025). The GDPR–FERPA compliance is not a legal obligation, as depicted in Figure 16. It is an essential prerequisite to responsible AI-enabled TQM governance.

To meet these requirements, institutions must establish data governance systems that implement various measures. Data governance systems must include anonymisation, role-based access, attribute-based access, encryption, audit trail and continuous monitoring tools so that the level of unauthorised access and data misuse can be reduced. In tandem, consent mechanisms must be clear, easily accessible, and sufficiently granular. This will allow students and staff to understand how their data are processed in AI-supported quality decisions (Popoola et al., 2024). In particular, students and staff must know how their data are collected, analysed, shared, retained, and used. In AI-driven quality systems, it is especially important that students must not always understand that predictive alerts or institutional quality indicators could be generated from their LMS activity, attendance patterns, service requests or feedback comments. So, ethical AI-TQM governance means making sure that data use is obvious and proportionate and serves an educational purpose not a surveillance one.

As put forth by the studies of Anastasiou and Ntokas (2024) and Didham and Ofei-Manu (2020), fairness in AI-supported decision making is another key ethical issue. If fairness is not actively managed, AI systems risk either reproducing historical inequalities or creating new forms of disadvantage. This includes disadvantage arising from ethnicity, gender, socioeconomic background, disability, language background or digital access. Accordingly, organizations should plan regular audits for bias detection, use balanced and representative training data, and have fairness toolkits that can help in the identification and reduction of model behaviour that yields discriminatory outcomes. Likewise, Chigbu and Makapela (2025) and Yusuf (2023) opine that fairness must answer transparency and explanation. It is not sufficient for an AI system to only generate correct outputs. It's not just the data that is important. Stakeholders need to understand where it came from, how the model works, and why it is producing certain decisions or recommendations.

In a university setting, we need Explainable AI (XAI) methods such as SHAP and LIME. An academic advisor should not receive only a risk score if an AI system notifies them that a certain student is 'at risk'. The advisor requires information on the reason for the alert. Was it due to falling grades, poor attendance, low LMS participation, missed assessments, financial hardship, delayed service requests or combinations of any of these? If this explanation does not take place, the advisor may respond generically or even aversely. Nevertheless, when SHAP or LIME highlights a few specific reasons behind the alert, the advisor can provide more ethical and more targeted help, such as academic tutoring, referral to counselling, financial support or administrative follow-up. As such, XAI makes sure that AI outputs are interpretable, actionable, and supervised by humans, thus supporting both fact-based decision-making and stakeholder-centred care.

Explanation also protects academic freedom and professional judgment. Recommendations from AI cannot be perceived as a decision that automatically replaces lecturers, advisors and quality officers. They ought to act as decision-support evidence that can be critiqued and contextualized by human experts. It's important because Student performance and institutional quality are shaped by complex academic, social, emotional, administrative factors. These cannot be captured fully through algorithms always. Thus, universities should document data sources, model structures, risk indicators, and decision criteria in a way that non-technical users can understand.

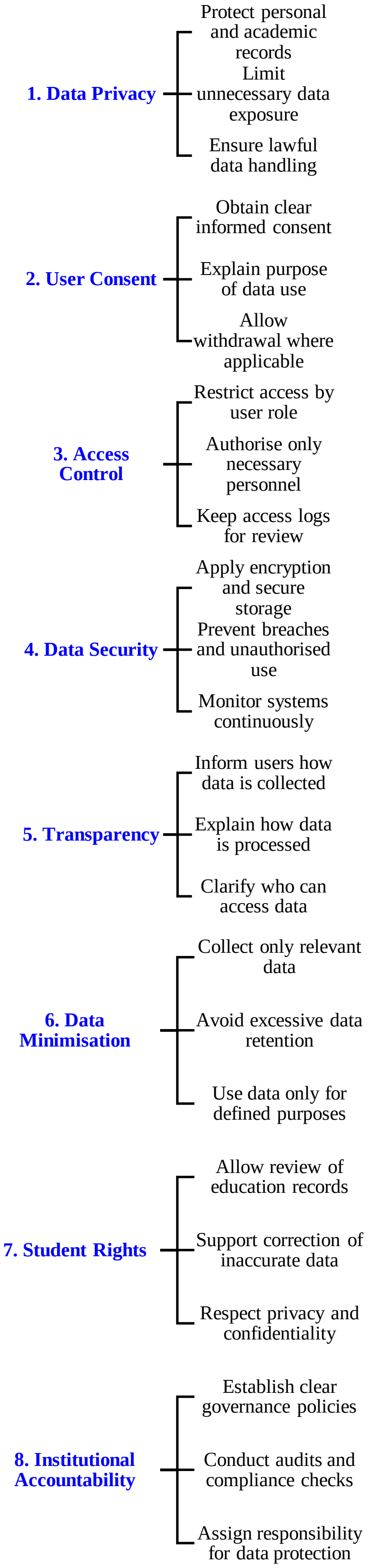

Figure 16: GDPR-FERPA Compliance Framework

Besides privacy, fairness, and transparency, strong governance is also necessary at the institutional level. According to Kadri et al. (2022), effective governance requires clear oversight at several levels, including the strategic, operational, and technical levels. At the strategic level, senior leadership should be responsible for policy direction, regulatory compliance, and institutional accountability. At the operational level, committees should oversee implementation quality, process alignment, and performance monitoring. At the technical level, specialised review groups should handle model validation, ethical checks, and audit cycles to ensure that AI systems remain aligned with institutional values and legal requirements (Kadri et al., 2022). In contrast to fragmented oversight, such a layered structure allows ethical and technical concerns to be managed in a more coordinated way. These governance dimensions are summarised in Table 8.

Table 8: Ethics & Governance Framework

Practice Area	Guideline	Implementation	Governance Level	Stakeholders	Tools & Techniques	Outcome
Data Privacy	Anonymization & Encryption	Role-based access, secure key management	Technical	IT, Data Stewards	AES Encryption, Tokenisation	Protected PII, compliance with GDPR/FERPA
Access Control	Role-Based & Attribute-Based Controls	RBAC/ABAC policies, audit logs	Operational	IT, Compliance Officers	IAM Systems, Audit Trails	Minimised unauthorised access
Consent Managemen	Transparent, Granular Consent	Dynamic consent dashboards, opt-in workflows	Operational	Students, Staff	Consent Management Platforms	Informed participation, trust enhancement
Data Security	Multi-Layered Security	Firewalls, IDS/IPS, and regular vulnerability scans	Technical	IT, Security Teams	SIEM, Penetration Testing	Reduced breach risk, timely threat detection
Fairness Auditing	Bias Detection & Mitigation	Fairness metrics, balanced datasets	Technical	Data Scientists, AI Teams	Fairness Toolkits (AI Fairness 360)	Equitable model outcomes
Transparency	Public Documentation of AI Processes	Maintain model cards and data lineage documentation	Strategic	Leadership, Faculty	Model Cards, Data Lineage Tools	Greater stakeholder understanding
Explain ability	Deploy XAI & Interpretability Methods	LIME, SHAP integration	Technical	AI Teams, Users	XAI Libraries	Clear decision rationales
Ethical Oversight	Regular Ethical Audits	Scheduled ethics reviews, compliance checks	Strategic	Ethics Board	Audit Frameworks	Sustained ethical compliance
Governance Committees	Multi-Tiered Oversight	Strategic, Operational, and Technical committees	Strategic	Leadership, Technical Teams	Governance Charters, Committee Portals	Coordinated decision-making
Stakeholder Roles	Defined Responsibilities	Role definitions, accountability matrices	Operational	Leadership, Faculty, Staff	RACI Charts	Clear roles, improved collaboration
Continuous Review	Iterative Policy & Process Refinement	Feedback loops, stakeholder consultations	Strategic	All Stakeholders	Surveys, Workshops, Ethics Panels	Adaptive, resilient governance
Audit Cycles	Integrated Technical & Ethical Audits	Combined security & ethics audits	Operational	Auditors, Compliance Teams	Combined Audit Tools, Checklists	Comprehensive oversight

Mökander and Floridi (2023) declare that repeated audit cycles, escalating pathways, and clear mandates can improve the effectiveness of governance structures. When the tool that uses anomaly detection or from the feedback of the stakeholders an AI setup features an ethical and operational problem, it usually emerges rapidly. So that, institutions should develop periodic audit schedules that are infused into the academic and administrative processes and establish clear protocols for the raising, reviewing and resolution of matters as they arise. For instance, if an AI model starts generating an increased number of risk alerts for a particular student group, programme or demographic category, this should raise a flag so it can be escalated for a fairness check before further use. Hence, AI Supported TQM should be a system accountable, rather than just automating systems.

Furthermore, governance should not be limited to formal committees only (Acharya et al., 2025; Gardezi, 2024). Organized involvement of stakeholders should also be done. Students ought to take part in co-designing the tools used for consent policy development, feedback mechanisms, and model interpretability. As a continuous process, faculty and administrative staff must engage in training and development programmes that enhance their abilities in artificial intelligence, ethics as well as the use of data. Technical teams should also partner with governance bodies to ensure policy expectations spark practical technical controls, validation procedures, and dashboard design.

Additionally, Popoola et al. (2024) argue that ethical governance must be a process rather than an act of compliance. As AI tools advance and social and regulatory expectations change, governance frameworks must also be modified accordingly. For this reason, institutions should develop ongoing ethical review systems, which includes recurring ethical assessments, stakeholder engagement, policy refinements, model monitoring, and explainability reviews. So, the ethical vigilance can become a part of the regular institutional quality cycle rather than a distinct activity carried out only after problems occur. Figure 17 displays the wider AI-TQM governance framework where adaptive review logic is illustrated.

When viewed collectively, the findings indicate that quality management (TQM)'s ethical use of AI cannot depend on its capability alone. Responsible AI-powered quality management relies on a combination of strong data governance and controls for fairness, transparency, and explain ability; a layered audit and consumer involvement; and ongoing ethical review Understanding how to verify the credibility of this information is very crucial for the higher education world, since this could impact student support, course decisions, resource allocation, academic advising and quality review. SHAP, LIME and any such XAI tools are not optional technical add-ons. Instead, they're the ethical safeguards that colleges have to ensure that AI-supported decisions remain comprehensible, revisable and supportive rather than opaque, punitive, or unfair. When these elements are seamlessly integrated, AI can enhance academic quality and operational efficiency without compromising the values of equity, autonomy, trust and institutional responsibility that are the heart of higher education.

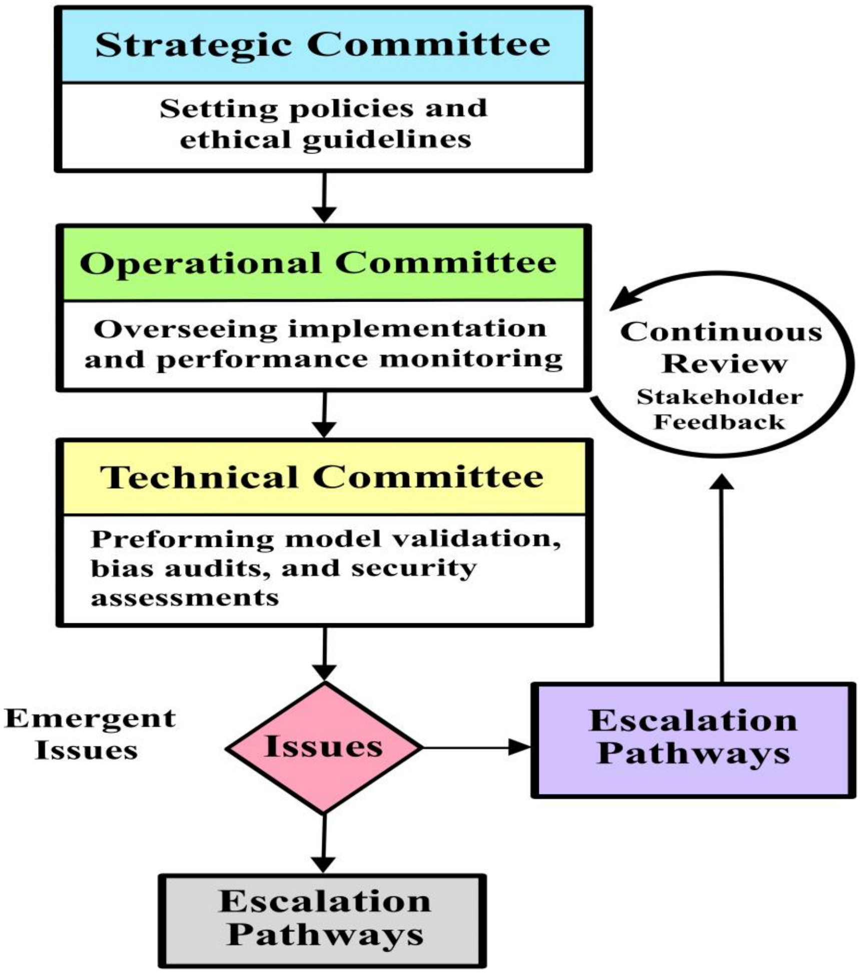

Figure 17: AI-TQM Governance Framework

Discussion

The main point of this review is that we cannot really improve the quality of education by just using Total Quality Management or Artificial Intelligence on their own. We need to combine them into one system that can adapt to changes. The papers we looked at show that Total Quality Management is still important for planning and making things better, but it is often slow and just done to follow the rules. On the hand Artificial Intelligence can help us find problems early make predictions and act faster. When we use Artificial Intelligence with the PDCA cycle we can make quality management more proactive.

What we see in the papers is that both TQM and AI have their benefits but combining them is even more powerful. TQM has been linked to students, more efficient administration and better relationships with stakeholders. AI has been linked to finding students who are struggling earlier giving them personalised support and making services more responsive. However, these benefits are often reduced when TQM is about following rules or when AI is only used in small pilot projects. The main benefit of combining them is that we get the structure of TQM and the predictive power of AI.

The papers also show that this combination works through mechanisms. First AI helps us respond faster to problems by finding them. Second it gives us a view of what is happening across different units by combining data. Third it helps us take targeted action by using predictions to inform our decisions. These mechanisms are especially important in education, where quality depends on many things like teaching, finance and governance.

At the time the review also highlights some inconsistencies and limitations in the research. While many studies show results much of the research is still theoretical or based on small pilot projects. There is a lot of variation in how studies are designed and what they measure. Some studies focus on student retention while others look at governance or administrative efficiency. This makes it hard to compare results directly. Additionally, universities are all different with varying levels of infrastructure, staff capability and resources. This is why some studies are more optimistic about combining TQM and AI while others are more cautious.

Another important point is that the main challenges are not just technical. While things like data quality and access are organisational barriers like low analytics literacy cultural resistance and resource constraints are just as significant. This means that we should not just treat AI enabled TQM as a technology project. As a transformation of the whole institution. It requires leadership commitment, staff capability and shared ownership across units.

The ethical dimension of this issue makes it more important. The research shows that privacy, consent, fairness, transparency and accountability are crucial in AI supported quality management. Universities deal with data and predictive systems can perpetuate inequality if we do not address bias. This is why we need governance frameworks from the beginning with policies, fairness audits and continuous ethical review.

From a perspective this review brings together two areas of research that have often been separate. TQM helps us understand how to organise and sustain quality while Artificial Intelligence explains how to make quality systems more predictive and data-driven. Their combination gives us a foundation for understanding quality management in higher education. From a perspective universities should take a phased approach starting with clarifying quality goals improving data readiness and piloting AI supported dashboards. From a policy perspective the findings suggest that we need standards for privacy, fairness and accountability before widely adopting Artificial Intelligence in higher education.

Overall, the evidence suggests that higher education is moving towards a phase of quality management, where old systems are no longer enough. What is clear is that TQM is still useful and that AI can significantly improve prediction, responsiveness and decision support. What is less certain is how consistently we can sustain this combination across institutions and under what conditions it can remain equitable and trustworthy. Future research should focus on long-term implementation, comparative evaluation, governance maturity and measurable effects, on administrative outcomes. The proposed Adaptive AI driven TQM cycle is a framework, but it still needs more empirical validation and testing.

Conclusion and Future Work

The integration of the artificial intelligence (AI) and total quality management (TQM) can reshape quality management in higher education as per the review. TQM has proven to be a sound basis for continuous improvement, but its traditional use tends to be slow and retrospective and is dependent on delayed results reporting. The foundation will be further strengthened through AI in real-time monitoring, predictive analysis, early intervention, and continuous feedback from stakeholders. As such, the Adaptive AI-Driven TQM Cycle is expected to be more agile and accommodating for enhancing quality in HEIs.

The value of this model in practice is that it gives university leaders a usable decision-making framework rather than a mere concept. A Dean can utilise the model for quality monitoring, detection of courses losing student interest, early identification of student withdrawal risks, and coordination of timely academic support. A Vice-Chancellor or member of the senior management team can use the model to connect the institutional data of academic departments, student services, finance, human resources, and quality assurance units into an integrated quality dashboard. This enables leadership to move from reporting of delays to governance of quality.

Put simply, the model supports four important functions of leaders. Firstly, it benefits leaders to prioritise issues arising from evidence rather than assumption. As a result, when student performance, satisfaction, signals decline, intervention happens faster. Third, accountability is enhanced by enabling identification of the unit responsible for any quality issue, along with details of action taken. It connects institutional performance indicators to real-time academic and administrative data, strengthening strategic planning. Consequently, the model can assist these institutions in enhancing student retention while improving service responsiveness, curriculum quality, staff coordination, and competitiveness.

There is a significant cost when organizations choose not to adopt this adaptive quality model. If universities rely solely on the conventional PDCA cycle, annual report, manual audit, and an array of siloed data systems, they may respond too late to disengagement of students, weaknesses in a programme, delays in service and dissatisfaction of stakeholders. Such a scenario could result in loss of students, a weak student experience, poor resource allocation, repeated problems in accreditation, lowered institutional reputation, and a slow response to labour market and technological changes. In the increasingly competitive and digital environment of higher education, delaying a quality action becomes more of a strategic risk than an operational weakness.

This assessment also indicates that the integration of AI and TQM is not only of technical nature. The successfulness of this depends on how the data integration, leadership will, staff capability, ethical governance, stakeholder participation, and so on, and collaboration, will be academic and administrative. The investigation revealed several barriers which included; data systems which were either disconnected, weak interoperability, limited analytics literacy, cultural resistance which was mostly due to the rigid organisational culture within various public health entities, unclear accountability, and ethical issues of privacy, fairness and explainability. Based on these findings, they should never be implemented as stand-alone technologies. They should view AI-enabled quality management as an institutional transformation that impacts governance, decision-making, staff roles, student support, and culture, not as a policy.

Deans should kick off the process with quality dashboards at the faculty level that link student engagement, course performance, feedback, attendance, assessment results and support-service data.

Senior academics and vice-chancellors must institutionalise an AI-TQM governance structure. This should cover data-sharing, data ethics reviews, staff training and ensuring accountability for all AI-supported interventions. For quality assurance units, the implication is to redesign quality cycles so that monitoring and corrective action occur continuously rather than only at semester end or at the end of the accreditation cycle.

This review also indicates that the evidence base remains in development at this stage. Most studies done to date are conceptual, exploratory, pilot based, or a single institutional case. We need more evidence on how AI-enabled TQM systems perform over time and across various types of higher education institutions. Some of the important questions that remain include fairness, explainability, trust, acceptance by staff, consent by students, and long-term impacts of AI-supported quality systems on education.

Future studies should focus on five main areas. There is a need to conduct longitudinal studies to evaluate the functioning of Adaptive AI-Driven TQM Systems in a real university. In addition, comparative research should be conducted across universities, countries as well as systems of governance to see which implementation models are most effective. Going forward, research must look at ethical and governance issues in greater depth, namely privacy, consent, algorithm fairness. partially computable explanatory models, human oversight. Researchers must assess the impact of AI-TQM systems at universities, not only on operational effectiveness but also on student success, university teaching quality, trust of stakeholders, staff workload and resilience of the institution. Fifth, universities should develop practical implementation guidelines and maturity models to allow them to adopt AI-enabled TQM responsibly, in a phased and context-sensitive manner.

To sum up, higher education institutions can no longer rely on quality management systems that are traditional, delayed and fragmented. The Adaptive AI-Driven TQM Cycle offers a useful framework for making quality management more agile, transparent, evidence-based, ethical, and student-centred. The proactive approach helps university executives to identify problems sooner, take faster actions, coordinate better, and enable continuous learning from institutional data. Only strong leadership, ethical governance, integrated data systems, staff development, and a clear commitment to human-centred quality improvement will help to make the model successful.

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Author Contributions

Tarek Elganas: Conceptualization, methodology, literature review, data curation, analysis, framework development, writing-original draft preparation, and correspondence. **Rob Moir**: Supervision, validation, critical review, editing, and academic guidance. **Abedalrhman Alkhateeb**: Review support, validation, writing-review and editing, and supervision.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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