



**Generative artificial intelligence (GenAI) to improve financial sustainability
of South African universities.**

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i. ABSTRACT

This study investigates how generative artificial intelligence (GenAI) can enhance the financial sustainability of South African public universities by addressing cost pressures and revenue challenges. A qualitative, exploratory design was adopted, involving nine semi-structured interviews with senior finance, technology and cyber security executives; the data were analysed thematically. Key findings indicate that GenAI can enable substantial cost savings (through automation of routine administrative financial tasks and data-driven budgeting) and create new revenue opportunities (such as AI-enabled products, online micro-courses, improved student recruitment, dynamic pricing, and targeted fundraising). However, success depends on factors like data quality, IT infrastructure, and staff skills. The study contributes to theory by linking AI adoption frameworks with university finance strategy and filling an empirical gap in research on GenAI in South African higher education finances. In practice, it offers a conceptual framework and recommendations to guide academic leaders in integrating GenAI into financial planning, providing actionable insights for balancing cost-efficiency and revenue generation in resource-constrained institutions.

ii. KEY WORDS

Generative artificial intelligence (GenAI); financial sustainability; South African universities; cost efficiency; revenue generation.

iii. PLAGIARISM DECLARATION

I declare that this research report is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Sibusiso Dantjie, 03 November 2025.

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CHAPTER 1: INTRODUCTION TO RESEARCH PROBLEM

1.1 Background and global context

Generative artificial intelligence (GenAI) represents a fast-advancing branch of AI that can generate text, images, and other forms of content that resemble work created by people. According to Kuyoro, Bagus, Benshir, and Bobat (2025), GenAI and related tools could add several trillion dollars to the global economy every year. In Africa, the 2025 McKinsey study suggests that, if institutions can overcome adoption challenges and expand their use of the technology, the continent might unlock between US \$61 billion and US \$103 billion in additional economic value across different sectors (Kuyoro et al., 2025). The same report notes that most African economies remain at an early stage of adoption, describing the region as only “scratching the surface” of what is possible (Kuyoro et al., 2025). These projections illustrate the strategic importance of GenAI for national competitiveness and public institutions. Higher education systems worldwide face increasing pressure to modernise and become more financially sustainable. In many countries, public universities have had to pursue cost reductions and develop new revenue streams against a backdrop of scarcity.

AI technologies are increasingly viewed as enablers of efficiency and improved decision-making within higher education. Recent studies indicate that these tools can simplify resource allocation, automate repetitive administrative work, and produce data insights that support more informed financial planning. Han, Xiao, Sheng, & Zhang (2024) emphasise AI’s role in reducing operational inefficiencies through automation and analytics, while Kumar, Rao, Singhania, Verma, & Kheterpal (2024) describe how GenAI has begun reshaping administrative processes. Supporting these findings, Verge AI (2025) reports that automation alone could cut administrative costs in higher education by as much as 30%. Together, these studies reinforce the idea that GenAI can help universities operate more efficiently even under financial pressure.

1.2 African higher education and the promise of AI

Although global enthusiasm for GenAI is high, adoption in African higher education remains limited, particularly in administrative and financial functions. Emerging evidence indicates that most African universities have concentrated their use of AI on teaching and student-facing areas such as learning analytics and intelligent

tutoring systems, while far less attention has been given to administrative or financial management. Kurien and Soglo (2024) note that AI initiatives across the region largely focus on the classroom, with very few extending into finance or operations. This limited adoption is often linked to weak infrastructure and policy constraints; many institutions still struggle with poor connectivity, unreliable data systems, and low digital capacity. Governance gaps (such as the absence of clear AI strategies) and under-developed regulatory frameworks add further complexity. In addition, skill shortages and limited research capability across sub-Saharan Africa slow down the deployment of advanced AI solutions. Butcher, Wilson-Strydom, and Baijnath (2021) also observe that outdated systems and minimal investment in AI-specific research continue to hold universities back.

Despite the technology's clear promise, African higher-education institutions have yet to take full advantage of AI for non-academic or administrative functions. Even South Africa, regarded as one of the continent's more digitally mature environments, faces similar hurdles. Although the Department of Communications and Digital Technologies (DCDT) introduced an AI policy framework in 2024, its implementation at university level is still in early stages. Limited budgets and infrastructure continue to restrict large-scale experimentation with AI-driven administrative tools. At the same time, South African universities are struggling with serious financial pressures that threaten their long-term stability. This intersection of technological potential and financial instability provides the backdrop for this research.

1.3 Financial sustainability of South African public universities

Public universities in South Africa occupy a central role in the country's development agenda. They serve as hubs for teaching, research, and innovation, and are vital to efforts aimed at reducing poverty and inequality (Motholo, 2023). Yet, in recent years, the financial stability of these institutions has come under increasing strain (Motholo, 2023). Growing competition for public funding has intensified, with higher-education budgets now competing directly against other pressing national priorities (Motholo, 2023). As a result, university leaders and policymakers are being forced to find new ways to manage limited resources more effectively and to sustain operations amid tightening fiscal conditions (Motholo, 2023).

Financial sustainability has therefore become a central concern for South Africa's public higher-education sector (Motholo, 2023; University A, 2022; University B,

2022; University C, 2022; University D, 2019). Declining subsidies, rising operational costs, and constrained tuition-fee income have made it difficult for universities to balance their budgets. Many institutions are now exploring alternative funding models, partnerships, and efficiency measures to maintain their academic and social missions while adapting to the realities of scarce public resources (Motholo, 2023; University A, 2022; University B, 2022; University C, 2022; University D, 2019).

1.3.1 Declining subsidies and rising costs

Universities in South Africa rely on three main income streams: state funding, student fees and “third stream income” (e.g., donations, commercial ventures) (Wangenge-Ouma & Kupe, 2020). A recurring theme across government and industry reports is that state subsidies, which constitute at least 40% of universities’ total revenue, have been declining in real terms (Motholo, 2023). The government has been under pressure to meet its subsidy obligations, leading to reductions in block grant allocations (1.07% in 2020/21 and 1.3% in 2021/22) to fund other priorities such as the growing cost of the National Student Financial Aid Scheme (NSFAS) (Motholo, 2023). Even where nominal allocations have increased (for example, a planned 0.9% increase to R40 billion for the 2023/24 academic year), enrolment growth and education specific inflation far outstrip funding increase (Motholo, 2023). On a per capita basis, universities are experiencing a funding decline (Motholo, 2023), creating what the Department of Higher Education and Training (DHET) terms an “unsustainable trend” (Motholo, 2023; University B, 2022; University A, 2022).

Operating costs at universities continue to climb. Staffing expenses (often shaped by national wage agreements) remain the single largest component of institutional budgets (University B, 2022). On top of that, the need to maintain buildings, utilities, and ongoing digital-transformation projects adds further financial weight. Motholo (2023) explains that increases in government subsidies have not kept pace with either enrolment growth or inflation, leaving universities increasingly dependent on tuition fees and external grants. This dependence exposes institutions to risks linked to student numbers and variations in funding flows.

Additional pressure comes from challenges within the National Student Financial Aid Scheme (NSFAS). Delayed disbursements and limited support for “missing-middle” students (those whose family incomes are too high for full assistance but too low to cover fees) have worsened financial strain across campuses. Whitelaw, Branson,

and Leibbrandt (2023) note that these delays and funding gaps create severe cash-flow constraints and add further uncertainty to university finances.

1.3.2 Student debt and affordability

Student fees form the second-largest source of income for universities, but fee increases are normally capped by government regulations linked to the consumer-price index. This limit reduces universities' ability to match their rising costs (Motholo, 2023). Economic downturns and the lingering effects of the COVID-19 pandemic have also weakened households' ability to pay, leading to mounting student debt and lower recovery rates (Motholo, 2023). By early 2023, the Minister of Higher Education reported that total outstanding student debt across South Africa's public universities had reached R16.5 billion (Motholo, 2023). Analysts foresee little improvement in the short term (Motholo, 2023). Unpaid fees erode cash flow and make it difficult for institutions to meet immediate obligations such as payroll and maintenance (Motholo, 2023; University A, 2022; University C, 2023).

1.3.3 Enrolment, throughput and infrastructure pressure

Financial sustainability is also affected by student enrolment patterns and completion rates. When students take longer to finish their studies, they occupy limited classroom, housing, and facility space for extended periods, restricting the intake of new students and therefore reducing tuition income and enrolment-linked subsidies (Motholo, 2023). Low or declining enrolment numbers also prevent universities from realising economies of scale, further tightening budgets (Motholo, 2023). To maintain financial stability, university leaders must improve recruitment, retention, and student support systems (Motholo, 2023). However, the pandemic and the rapid move to emergency remote teaching introduced additional barriers to student engagement and completion (Motholo, 2023).

1.3.4 NSFAS and the “missing middle”

The NSFAS provides funding for students from households earning below R350 000 per year (Motholo, 2023). Demand for this assistance far exceeds the available resources, making the funding model structurally fragile (Motholo, 2023). To manage the shortfall, government has redirected money from university block grants and earmarked funds, thereby reducing direct institutional subsidies (Motholo, 2023). Recent NSFAS policy changes (including caps on residence fees and adjustments to programme funding) have further constrained university finances (Motholo, 2023).

These administrative complications create continuing uncertainty for both students and institutions (Motholo, 2023).

1.3.5 Historical and macroeconomic factors

Even before the pandemic, South African universities were already confronting deep-rooted financial sustainability challenges. An analysis by Wangenge Ouma and Kupe (2020) explains that universities' financial resources are critical for fulfilling their roles. Even before COVID 19, institutions faced declining state funding (in real terms), the aftermath of the #FeesMustFall protests, insourcing of services, regulation of tuition fees, rising student debt, weak economic growth and a volatile currency (Wangenge-Ouma & Kupe, 2020). The pandemic aggravated these conditions by introducing additional uncertainty and economic contraction, making every funding stream more precarious (Wangenge-Ouma & Kupe, 2020).

As a result, universities now operate within increasingly fragmented funding systems where every revenue stream is under strain (Wangenge-Ouma & Kupe, 2020). In summary, South African universities face a difficult financial position, trapped between limited public funding and the restricted ability to raise tuition fees without undermining access (University B, 2022). These pressures threaten their capacity to deliver on teaching and research commitments (Wangenge-Ouma & Kupe, 2020). Collectively, these realities highlight an urgent need for innovative approaches that can control costs, broaden income sources, and build long-term institutional resilience.

1.4 Potential of generative AI for university finances

The digital transformation of higher education has opened new ways to address long-standing financial challenges. GenAI shows particular promise because it can produce human-like text, manage complex administrative tasks, and analyse extensive datasets with speed and accuracy. This research therefore focuses on two areas where GenAI could strengthen financial sustainability: cost optimisation and revenue enhancement.

1.4.1 Cost optimisation

Emerging evidence and recent industry analysts suggest that GenAI can substantially reduce administrative workloads and improve operational efficiency (HolonIQ, 2023). By automating repetitive paperwork, generating standardised

reports, and handling routine queries through chatbots, GenAI enables university staff to focus on more value-adding activities. These systems can also analyse large datasets (such as financial records and maintenance logs) to detect inefficiencies and recommend savings, effectively providing predictive analytics for resource management (HolonIQ, 2023).

Shoaib, Sayed, Singh, Shafi, Khan, and Ali (2024) observe that GenAI models minimise human error and streamline internal processes within financial institutions, insights equally applicable to university administration. Similarly, Verge AI (2025) estimates that AI-based process automation could cut administrative costs in higher education by as much as 30%. Beyond these operational gains, GenAI offers predictive support for infrastructure maintenance, budgeting, and procurement planning (Patterson et al., 2025). By managing such functions more effectively, universities could better control staffing costs and allocate resources with greater strategic precision.

1.4.2 Revenue enhancement

GenAI provides new avenues for universities to expand and diversify their revenue sources. Personalised, AI-driven marketing tools can enhance student recruitment and retention by identifying prospective students more accurately and flagging at-risk learners for timely support. Saúde, Barros and Almeida (2024) and Batista, Mesquita and Carnaz (2024) demonstrate that AI-enabled personalisation can increase throughput rates and secure tuition income.

GenAI can also support the rapid creation of online micro-credential programmes and interactive simulations, opening opportunities to reach new learner markets (including professionals and international students) while generating additional fee income. It can also support research commercialisation and consulting activities by accelerating data analysis and proposal writing. Studies by Hannan and Liu (2023) and George and Wooden (2023) note that AI is becoming a differentiator among higher education institutions, enabling them to innovate in program offerings and student experiences. Farrelly and Baker (2023) add that generative AI enhances international outreach and student support, indirectly improving institutional reputation and enrolment. Overall, these varied applications highlight generative AI (GenAI)'s ability not only to contain operational costs but also to unlock new income streams that reinforce institutional financial sustainability.

1.4.3 Underexplored applications and research gap

Although GenAI holds significant promise, its direct application to the financial sustainability of universities remains largely underexplored. Most available insights originate from global studies or analysis conducted in other sectors. Existing research tends to focus either on general artificial intelligence or on machine-learning applications that address financial management issues without explicitly considering GenAI, or else it examines AI use in fields such as banking (Kumar et al., 2024).

Kumar et al. (2024) observe that limited knowledge exists on how GenAI could be leveraged within university financial management. Similarly, Shoaib et al. (2024) and Renkema and Tursunbayeva (2024) highlight AI's role in predictive analytics and institutional decision-making but note that these studies seldom address the broader question of financial sustainability. Therefore, while GenAI's potential is widely discussed, there is still little empirical evidence demonstrating whether and how its adoption can strengthen financial sustainability across universities (even more so in resource constrained environments like South Africa).

This absence of focused research defines the core gap that this research aims to address. Addressing this gap requires both a theoretical framework and practical insights into how decision makers (in South African universities) perceive and could deploy GenAI.

1.5 Business rationale and urgency

The challenges outlined in Section 1.3 present a significant business concern for South African universities. Declining government subsidies, escalating operating costs, rising student debt, and unstable funding streams continue to threaten institutional viability (University A, 2022; University C, 2023). Traditional cost-cutting measures and gradual revenue-growth strategies have proven inadequate to meet these pressures.

University leaders therefore face increasing pressure to find innovative ways to lower expenses and broaden income sources. As central hubs for national knowledge creation and skills development, universities cannot simply scale back or suspend activities without undermining economic progress and social equity (Motholo, 2023). The ongoing financial strain heightens the urgency (University A, 2022; University C, 2023) to identify new approaches (such as the adoption of GenAI) to sustain operations and fulfil public mandates.

The business rationale for this research is thus to explore whether, and in what ways, GenAI can enable universities to control costs, expand revenue streams, and strengthen their long-term financial resilience.

1.6 Theoretical rationale and contribution

From an academic perspective, the intersection of GenAI, higher education management and financial sustainability represents an under theorised domain. Existing studies have established that AI can enhance administrative efficiency and support decision making, but few have conceptualised a framework for integrating GenAI into university financial strategies. Theoretical work in this area could contribute to several literatures: (1) digital transformation of higher education; (2) technology adoption in complex organisations; and (3) financial management in resource constrained institutions. By analysing how GenAI can simultaneously address cost inefficiencies and unlock new revenue streams, the research aims to extend the understanding of how emerging technologies can reconfigure financial ecosystems. As highlighted by Han et al. (2024) and Hannan and Liu (2023), there is a growing need to deepen understanding of how emerging technologies can reshape financial systems.

In line with this call, this research aims to contribute empirical evidence drawn from a developing-country perspective, thereby addressing the current geographical gap in research on GenAI and university financial sustainability. This research will yield a conceptual framework grounded in decision makers' perceptions and experiences; such a framework can guide future quantitative testing and comparative studies not only in higher education, but also in other sectors or regions.

1.7 Scope and delimitations

The research focuses on South African public universities. Private universities and other African countries are excluded to maintain contextual depth and comparability. The term "Generative AI" refers to advanced machine learning models capable of producing human like content (e.g., large language models such as GPT 4). Traditional AI and analytics tools are beyond the core scope except where they overlap with generative functionalities. The research emphasises two financial domains (cost management and revenue generation) because they represent the main levers for improving financial sustainability.

Elements such as teaching quality, academic freedom, and student discipline fall outside the boundaries of this research. The research adopts an exploratory, qualitative design that centres on the perspectives and lived experiences of university decision-makers rather than testing predetermined hypotheses. It does not involve the implementation of GenAI technologies; instead, it aims to develop a conceptual framework and a set of practical guidelines informed by stakeholder insights.

1.8 Significance of the research

1.8.1 Practical significance

The findings are expected to equip university leaders, policymakers, and technology partners with practical, evidence-based insights on how to apply GenAI to strengthen financial sustainability within higher-education institutions. By detailing how GenAI can reduce administrative costs and create new income streams, the research may help institutions prioritise investments, design pilot projects and negotiate partnerships with technology vendors. The research further responds to the urgent need to balance financial resilience with equitable access. By generating insights into cost efficiencies, it may assist universities in maintaining affordability for students while upholding the quality of teaching and institutional outcomes.

1.8.2 Theoretical significance

Academically, the research contributes to an emerging body of literature on GenAI adoption in complex public organisations. It will formulate a conceptual framework that articulates the relationships between GenAI capabilities, cost optimisation and revenue enhancement within higher education finance. The proposed framework has the potential to guide future theoretical developments and quantitative studies, extending its relevance beyond South Africa to other regions. Moreover, it brings together perspectives from technology management and financial strategy, thereby strengthening interdisciplinary dialogue and scholarly collaboration.

1.9 Structure of the research report

Chapter 1 – Introduction: Introduced the research problem and justified its importance in both practical and theoretical terms. It has described the economic and institutional context of South African universities, outlined the potential of GenAI for cost and revenue improvement, and described the research gap.

Chapter 2 – Literature review: Synthesises existing research on AI and GenAI in higher education, focusing on financial sustainability, cost efficiency, and revenue diversification. It reviews theoretical frameworks linked to technology adoption and financial management, identifying where current scholarship falls short in addressing the unique realities of South African public universities.

Chapter 3 – Research questions, propositions and hypotheses: Presents the research's main and subsidiary research questions, explaining the rationale underpinning each. It also outlines the theoretical perspectives that guided data collection, analysis, and interpretation.

Chapter 4 – Research methodology: Details the research design, philosophical stance, and methodological approach. It discusses the sampling framework, unit of analysis, data collection procedures, and analytical techniques, as well as the measures implemented to ensure quality, reliability, and ethical compliance.

Chapter 5 – Findings: Reports the empirical results emerging from the research. It presents insights related to cost management and efficiency (RQ1), revenue generation and diversification (RQ2), and cross-cutting themes such as barriers, enablers, and contextual factors influencing GenAI adoption.

Chapter 6 – Discussion of results: Interprets the findings in relation to the theoretical framework and prior literature. It explores how the outcomes address the research questions, identifies implications for theory and practice, and analyses the institutional enablers and obstacles affecting GenAI implementation in South African universities.

Chapter 7 – Conclusions and recommendations: Summarises the key findings and their relevance, situates the research within the broader academic and practical context, and proposes recommendations for policymakers, university leaders, and practitioners. It also acknowledges research limitations and suggests directions for future research, concluding the report with final reflections.

CHAPTER 2: LITERATURE REVIEW

This chapter reviewed current literature to clarify what was known and unknown about generative artificial intelligence (GenAI) and university financial sustainability. It positioned the current research within the existing debates and set out the theoretical and contextual foundations for the research. A literature review is not a general tutorial but an argument; its purpose was to demonstrate that a serious gap existed, refine the research problem and lead logically to the research questions. The structure began with theory, then moved from global literature to the African and South African contexts, before focusing on how GenAI could improve costs and revenues. Cross-cutting enablers and barriers were examined to provide a balanced view of factors influencing AI adoption within higher education. The chapter concluded by identifying the key research gaps and clarifying the research's anticipated contributions. This structured approach ensured that the literature review explained the central research problem rather than simply summarising existing studies.

2.1 Theoretical foundations

Sound research requires a clear theoretical foundation that frames interpretation and positions findings within the broader body of scholarly debate. Three theoretical perspectives were therefore reviewed: the resource-based view (RBV), diffusion of innovation (DOI) theory and the technology acceptance model (TAM). The RBV argues that organisations achieve sustainable advantages by acquiring and deploying valuable, rare and unique resources (Barney, 1991). Within the university context, GenAI tools (along with the accompanying data, technical capabilities, and human expertise) can be viewed as strategic resources that, when effectively leveraged, have the potential to strengthen institutional financial performance. The DOI theory (Rogers, 2003) provides a useful lens for understanding how new ideas and technologies spread within social systems. It highlights attributes such as relative advantage, compatibility, and complexity as key determinants of adoption. DOI has been extensively applied in research on educational technology uptake, offering insights into how GenAI initiatives could gradually gain institutional acceptance across universities. Complementing this, the TAM (Davis, 1989; Venkatesh & Davis, 2000) states that users' behavioural intentions toward adopting a technology are influenced primarily by their perceptions of its usefulness and ease of use. In the context of this research, TAM helps explain how higher education

leaders evaluate GenAI; balancing its perceived benefits for efficiency and financial sustainability against concerns about risk, effort, or organisational readiness.

These theoretical perspectives suggest that GenAI adoption extends beyond technical deployment; it is a socio-technical process requiring adequate resources, institutional alignment, and user acceptance to achieve meaningful transformation. They also emphasised that sustainable financial benefits depend on universities' capabilities and strategic fit rather than technology alone, a theme that emerged strongly in the interviews and in Chapter 6.

While the RBV, DOI, and TAM offer valuable theoretical perspectives for examining technology adoption, scholars have also pointed out important limitations in their application. The RBV, in particular, has been critiqued for presenting a relatively static understanding of organisational resources and for overlooking the dynamic influence of external environmental conditions on competitive advantage (Priem & Butler, 2001). In the context of universities, the RBV emphasises the need to acquire AI related resources such as data and skills, but it does not fully explain how public institutions with constrained budgets can build these capabilities. DOI has been faulted for focusing on adoption at the individual or organisational level without adequately considering systemic inequalities that influence technology diffusion (Greenhalgh, Wherton, Papoutsis, Lynch, Hughes, Hinder, & Shaw, 2017). For instance, perceptions of relative advantage and compatibility may differ significantly between well-resourced urban universities and those located in rural or underfunded contexts.

The TAM has likewise faced criticism for its assumption of rational and individualistic decision-making, which tends to overlook the influence of organisational culture, social dynamics, and power relations in shaping technology adoption (Bagozzi, 2007). Acknowledging these critiques is essential, as they highlight the need for analyses of GenAI adoption to move beyond simplified acceptance models. Such evaluations should also account for institutional constraints, regulatory environments, and ethical considerations that affect how these technologies are implemented within higher education systems. The following sections therefore integrate these theoretical insights while remaining sensitive to their boundaries.

Beyond noting these limitations, it is necessary to synthesise the theories and recognise that they complement each other rather than operate in isolation. The RBV

emphasises that sustainable advantage arises from resources that are rare, valuable, and difficult to imitate. However, it offers limited insight into how these resources evolve over time or how organisations adjust and reconfigure them in response to changing environmental conditions. The dynamic capabilities perspective, which has been applied in digital transformation research, emphasises that organisations must sense opportunities, seize them and reconfigure resources to respond to technological disruption. When considered together, RBV and dynamic capabilities suggest that universities will benefit from GenAI only if they continuously upgrade their data infrastructures, staff skills and organisational routines.

Similarly, the DOI framework identifies the factors that influence the rate at which new technologies are adopted, yet it does not fully explain why certain institutions lack the internal capabilities or resources required to implement such innovations. Integrating DOI with the RBV highlights that perceptions of relative advantage and complexity are often shaped by an institution's resource base and broader organisational context. The TAM, on the other hand, focuses on individual perceptions of usefulness and ease of use but tends to overlook the influence of social norms, institutional hierarchies, and power dynamics. Combining TAM with DOI allows researchers to examine how factors such as leadership commitment, organisational culture, and stakeholder expectations mediate technology acceptance processes.

Accordingly, this research adopts a pluralistic theoretical stance, acknowledging that no single framework can fully capture the socio-technical complexity surrounding the adoption of GenAI within university environments. A critical perspective is needed to interrogate not only whether GenAI is useful or easy to use but also who benefits, who may be disadvantaged, and how institutional resources and norms shape these outcomes.

2.2 Global perspective on AI's role in higher education finance

Around the world, artificial intelligence has been promoted as a catalyst for improving efficiency and decision making in higher education management. Recent research indicates that AI systems can automate repetitive administrative and analytical tasks, minimise human error, and produce data-driven insights that enhance financial planning and decision-making. For example, Han et al. (2024) emphasised that AI has the potential to improve efficiency in university financial management by

automating routine processes and generating analytical insights that support cost reduction and resource optimisation. Kumar et al. (2024) observed that GenAI might revolutionise administrative workflows, and by so doing enable more strategic financial planning and help institutions to “do more with less”. Industry and university reports reinforced these claims (University B, 2022). Verge AI (2025) observed that AI technologies can automate repetitive administrative activities such as invoice processing, scheduling, and report generation, thereby enabling staff to focus on higher-value strategic work. Similarly, HolonIQ’s (2023) global survey on educational AI found that generative models have the potential to enhance efficiency across multiple university departments by handling large volumes of routine tasks. Taken together, these studies suggest that GenAI could enable universities to lower operational costs through streamlined back-office processes and more informed decision-making.

In addition to these cost-related benefits, global research has also begun to highlight AI’s capacity to create new revenue opportunities for higher-education institutions. Studies pointed out that AI driven personalisation could improve student recruitment and retention, leading to more stable tuition revenue. Saúde, Barros and Almeida (2024) and Batista, Mesquita and Carnaz (2024) argued that AI tools could personalise marketing and learning support, reducing dropout rates and boosting enrolment. Hannan and Liu (2023) observed that AI could differentiate universities by enabling innovative program offerings and personalised learning experiences, which in turn attract students and funding. George and Wooden (2023) added that AI could enhance international outreach and student support, indirectly contributing to financial health through higher reputation and enrolment. Farrelly and Baker (2023) observed that GenAI could create new revenue opportunities for universities through offerings such as micro-credentials, digital short courses, and consulting services.

However, most of these publications described potential use cases and early pilot projects rather than providing systematic, peer-reviewed evidence. Much of the global literature focuses on isolated efficiency gains or academic applications of AI and seldom addresses the wider question of institutional financial sustainability. Few studies have examined how GenAI might respond to persistent funding shortfalls or structural budget deficits in higher education. This gap underscores the need for

context-specific investigations into GenAI as a strategic tool for managing systemic financial pressures.

Before narrowing the discussion to the African context, it is necessary to critically assess the global evidence base. Although the works reviewed above highlight AI's capacity to streamline operations and unlock new income streams, much of this material originates from industry reports or limited pilot initiatives. These sources may reflect vendor perspectives and often lack the methodological rigour typical of peer-reviewed research. Even where academic studies exist, they tend to concentrate on discrete administrative areas rather than on comprehensive institutional outcomes. Recent research also draws attention to unresolved barriers involving implementation costs, technical infrastructure, data governance, and algorithmic bias (Kalniņa, Nīmante, & Baranova, 2024). Scholars caution that unchecked enthusiasm for GenAI can obscure the hidden costs of system upgrades and staff training, while neglecting ethical dimensions such as privacy, fairness, and transparency. Overall, the global literature portrays GenAI as promising but incomplete. Determining whether it can genuinely enhance financial sustainability therefore requires context-sensitive research that weighs potential advantages against associated risks.

Beyond the economic and technical dimensions, a growing stream of scholarship has also begun to document the social and environmental implications of GenAI. Francis, Jones, and Smith (2025) describe the technology's "dual-edged" nature, noting that its expansion raises new challenges related to academic integrity, equity, and responsible use within higher education. They cautioned that GenAI might undermine the authenticity of student work and worsen existing inequalities by privileging those with greater digital access (Francis, Jones, & Smith, 2025).

The same review also identified broader ethical and sustainability concerns linked to the use of AI in higher education (Francis, Jones, & Smith, 2025). These include the risks of algorithmic bias, the widening digital divide, and the environmental footprint of large-scale computing systems (Francis, Jones, & Smith, 2025). Such issues mirror a growing body of critical scholarship that questions the opacity of AI algorithms, the spread of misinformation, and the potential for automated decision-making to entrench existing social inequalities (Francis, Jones, & Smith, 2025). And, the training of large generative models has been associated with high energy consumption and considerable carbon emissions, raising legitimate doubts about the

environmental sustainability of AI adoption (Francis, Jones, & Smith, 2025). These challenges are crucial when assessing GenAI's financial appeal; while automation may deliver operational savings, those gains could be offset by hidden social and ecological costs.

Taken together, these insights point to the need for a more nuanced understanding of the global literature; one that recognises both the efficiency benefits and the ethical dilemmas embedded in GenAI adoption. This balance highlights the importance of comprehensive governance frameworks that explicitly address issues of privacy, bias, equity, and environmental responsibility.

2.3 AI in African higher education: opportunities and barriers

The adoption of AI across African higher education remains limited and uneven. Existing studies indicate that most institutions have concentrated their AI efforts on teaching, learning, and student-support functions, while financial and administrative applications are still rare. Kurien and Soglo (2024) found that AI initiatives in African universities primarily target student-facing systems, with progress constrained by policy gaps, infrastructural weaknesses, and shortages of digital skills.

Many universities continue to grapple with outdated technological infrastructure, low internet bandwidth, and unreliable data systems; all of which restrict the effective deployment of advanced AI tools. Butcher, Wilson-Strydom, and Baijnath (2021) similarly observed that limited research capacity and legacy information systems across sub-Saharan Africa remain key barriers to realising AI's potential. Collectively, this body of work portrays a region that recognises the promise of AI but has yet to translate that awareness into meaningful transformation beyond academic and academic domains.

Recent commentaries emphasised that African universities needed to move beyond pilot projects and mainstream AI into education systems.

A 2025 article published in CIO Africa argued that the continent must move beyond high-level strategies toward practical implementation by deploying AI-driven models that are adaptive, data-centric, and culturally contextualised (Sahai, 2025). The article noted that mobile internet access across Africa remains uneven, particularly in rural regions, and recommended the development of lightweight, low-bandwidth AI platforms to help bridge connectivity divides (Sahai, 2025). It further emphasised the African Union's Continental AI Strategy and recent regional policy dialogues that

call on member states to establish ethical frameworks, strengthen data-governance mechanisms, and promote cross-sector collaboration (Sahai, 2025). The same report also highlighted tangible investment initiatives (such as Microsoft's campaign to train one million South Africans in AI skills and expand cloud data-centre capacity) as examples of ongoing efforts to build the digital infrastructure and human capability necessary for sustainable adoption (Sahai, 2025). Taken together, these insights underscore that robust infrastructure, clear policy direction, and sustained capacity development remain essential prerequisites for scaling AI adoption across the African higher-education landscape.

Broader international research reinforces this regional perspective. The EY–FICCI “Future-Ready Campuses” report, which surveyed leaders in Indian higher education, found that successful AI integration depends on embedding AI literacy across disciplines, investing in robust digital infrastructure, and cultivating collaborative innovation ecosystems (EY-Parthenon, 2025). The report further emphasised the importance of reskilling faculty, redesigning curricula, and strengthening data infrastructure and governance to uphold principles of fairness, transparency, and accountability (EY-Parthenon, 2025). Although the report's primary focus was India, its insights resonate strongly within the African context, where universities encounter similar readiness and capacity constraints. Collectively, the African and global literature underscore that without reliable infrastructure, adequately skilled personnel, and coherent policy support, AI initiatives are unlikely to produce sustainable financial benefits for higher-education institutions. These contextual factors were therefore explored in the findings (Chapter 5) and discussed in Chapter 6 as cross cutting enablers and barriers.

Before moving to the South African context, it is useful to reflect on the diversity of views within the African AI literature. Several commentators describe Africa's potential to leapfrog traditional development pathways by leveraging AI for personalised learning and large-scale student support systems (Sahai, 2025). At the same time, others caution that persistent digital divides and limited technological resources may exacerbate existing inequalities (Sahai, 2025). According to Sahai (2025), mainstreaming AI across the continent requires moving beyond policy rhetoric toward tangible investment in lightweight, low-bandwidth platforms and stronger cross-sector collaboration. Policy frameworks such as the African Union's Continental AI Strategy similarly advocate for ethical adoption, sound data-

governance practices, and inclusive implementation approaches (Sahai, 2025). These contrasting viewpoints indicate that the impact of AI in Africa will largely hinge on political will, infrastructure investment, and sensitivity to cultural context. They also serve as a reminder that importing global AI solutions without adaptation risks overlooking linguistic diversity, socio-economic realities, and ethical complexities; a concern echoed by Kalniņa, Nīmante, and Baranova (2024) in recent discussions on the cultural and moral dimensions of AI.

The critical literature further cautions that inadequately adapted GenAI models risk reproducing existing social and cultural power imbalances. Scholars contend that AI systems trained primarily on Western datasets may embed linguistic and cultural biases, thereby marginalise local knowledge systems and reinforce what some have termed “AI colonialism”. Francis, Jones, and Smith (2025) argue that GenAI could deepen the digital divide by privileging users with stable internet connectivity and advanced computing resources, while leaving rural and under-resourced institutions even further behind. Their review also warns that bias within training data threatens inclusivity and undermines current movements to decolonise higher-education curricula. For African universities, these critiques highlight the importance of designing and deploying AI solutions that respect local languages, cultural values, and ethical frameworks. They likewise point to the need for regional data-governance mechanisms that safeguard data sovereignty and prevent the extraction of indigenous knowledge without fair reciprocity.

By situating GenAI within broader debates on equity, autonomy, and epistemic justice, the literature encourages a more critical and context-sensitive engagement with both the opportunities and risks of AI in African higher education. Such reflection is vital to avoid reproducing global inequalities under the guise of technological progress.

2.4 Financial sustainability challenges facing South African universities

South Africa’s public universities exemplify the financial pressures confronting higher education institutions in developing economies. Over the past decade, government block grants have failed to keep pace with enrolment growth and inflation, resulting in a real decline in funding per student. At the same time, operational costs (including staff salaries, infrastructure maintenance, and utilities) have increased at rates

exceeding inflation. Consequently, many institutions now face persistent budget constraints and rising deficits.

Student fees, the second major revenue source, are also under pressure. Affordability concerns and ongoing political debates have constrained universities' ability to implement fee increases, while high levels of unpaid tuition continue to undermine institutional cash flow. Collectively, student debt across the system has grown into several billions of rand. The NSFAS provides crucial support for low-income learners, yet recurring funding shortfalls and administrative delays have widened the so-called "missing-middle" gap, leaving many students without adequate financial assistance. Whitelaw et al. (2023) noted that these systemic challenges (combined with delayed disbursements) have amplified universities' overall financial vulnerability. In short, South African universities are experiencing declining revenue alongside escalating costs, making financial sustainability an urgent and structural concern and prompting exploration of innovative responses such as GenAI.

While the factors above reflect long-standing structural funding imbalances, a series of external shocks has further intensified the crisis. The COVID-19 pandemic forced universities to transition rapidly to online teaching, generating unforeseen expenses for digital infrastructure, devices, and connectivity. Simultaneously, ongoing power disruptions and escalating energy prices (linked to the national electricity crisis) have inflated operating costs related to backup power, technology maintenance, and campus security. Macroeconomic pressures such as inflation and currency depreciation have also weakened purchasing power, particularly for imported technology and research equipment. These cumulative shocks illustrate that financial sustainability is not a transient issue but a systemic challenge requiring both rigorous cost management and diversified income strategies (Motholo, 2023).

Within this context, emerging technologies like GenAI warrant exploration for their potential to enhance efficiency and balance affordability with access. However, any technological intervention must be critically assessed against broader socio-economic realities and the possible unintended consequences of automation within the South African higher-education environment.

2.5 Generative AI for cost optimisation

2.5.1 Automating administrative tasks

Studies have widely recognised that GenAI can reduce administrative costs by automating routine tasks. Han et al. (2024) observed that AI systems could handle processes like invoice processing, scheduling and reporting, thereby freeing staff time and reducing errors. Verge AI (2025) provided examples of AI automating standard reporting and basic communications, showing that these tasks, when delegated to AI, save labour and lower overheads. HolonIQ (2023) similarly observed that educational applications of AI can automate high-volume administrative functions across departments, thereby improving institutional efficiency. In a related study examining AI use in organisational environments, Mohsen, Hamdan, and Shoaib (2025) found that generative models reduce the likelihood of human error while streamlining day-to-day operations.

Applied to the university context, these insights suggest that tasks such as student enrolment processing, invoice reconciliation, and the drafting of routine correspondence could be automated through GenAI systems. This would enable administrative staff to redirect their efforts toward higher-value strategic and student-focused activities, ultimately enhancing overall productivity and service quality within the institution.

2.5.2 Data driven budgeting and analytics

Beyond automation, the literature pointed to AI's ability to analyse large datasets and provide decision support. Shoaib et al. (2024) found that AI systems minimise human error and streamline operations in financial institutions, suggesting that such analytics could guide budgeting in universities. Mohsen et al. (2025) argued that AI driven analytics can pinpoint inefficiencies and support cost effective operations.

Within a university context, AI can be applied to analyse procurement and expenditure data to uncover inefficiencies, identify underutilised assets, and flag operational processes that contribute to unnecessary costs. Han et al. (2024) emphasised that intelligent financial systems have the potential to transform management practices by relieving staff of repetitive administrative duties and reducing the risk of human error. Building on these insights, GenAI could function as a "fine management" instrument; offering budget managers real-time, data-driven

intelligence to guide spending decisions, strengthen accountability, and enhance financial oversight across the institution.

2.5.3 Procurement, scheduling and resource optimisation

GenAI also demonstrates significant potential in optimising procurement and resource management processes within universities. Mohsen et al. (2025) suggested that AI can optimise procurement through contract analysis and supplier evaluation. Shoaib et al. (2024) and HolonIQ (2023) observed that AI technologies can automate key procurement functions such as invoice matching, detection of duplicate purchases, and the identification of more cost-effective suppliers. Beyond procurement, AI-enabled scheduling and resource allocation tools can optimise the use of classrooms, utilities, and facilities, in so doing reduce operational waste and lower recurring costs. These examples demonstrate that cost optimisation through AI is not confined to human resource management but extends across the full spectrum of university operations (from procurement and facilities management to financial administration and service delivery).

When combined with predictive analytics, universities can forecast demand for services and adjust procurement accordingly. Although the literature described these possibilities broadly, empirical evidence from this research began to fill the gap by documenting how South African universities have explored such AI tools in pilot projects, thereby grounding the theoretical promise in real contexts.

2.6 Generative AI for revenue generation and diversification

2.6.1 Student recruitment and retention

One of the most promising revenue-generation opportunities offered by GenAI lies in its potential to strengthen student recruitment and retention strategies within universities. Saúde, Barros and Almeida (2024) and Batista, Mesquita and Carnaz (2024) argued that AI tools can personalise marketing to prospective students and provide timely support to those at risk of dropping out. Personalised outreach can attract applicants who are more likely to enrol and succeed, while early warning systems can reduce attrition, thereby safeguarding tuition income. Hannan and Liu (2023) observed that AI can enable universities to differentiate their programme offerings and personalise student support, thereby enhancing their ability to attract both enrolments and external funding. Similarly, Farrelly and Baker (2023) highlighted that GenAI tools can strengthen student engagement, improve academic

support services, and expand international outreach through more targeted and adaptive communication strategies.

2.6.2 Developing new programs and services

GenAI enables universities to expand their programme offerings more rapidly and cost-effectively than through traditional course development approaches. Saúde, Barros, and Almeida (2024) suggested that generative models can assist in producing educational materials and realistic simulations for online micro-credentials and short courses. Likewise, Batista, Mesquita, and Carnaz (2024) observed that AI technologies facilitate the swift creation of digital learning content for micro-credentials and professional education programmes, helping institutions respond quickly to evolving labour-market demands.

Farrelly and Baker (2023) highlighted the possibility of launching AI powered virtual lab experiences or chatbot services that could be commercialised or licensed to other institutions. Hannan and Liu (2023) contended that AI driven innovation in program offerings is becoming a differentiator among universities. By creating new products and services, universities could generate third stream income and diversify their revenue base.

2.6.3 Optimising core revenue and dynamic pricing

Another potential revenue avenue lies in optimising existing income streams. AI-driven analytics can help universities identify students who are most at risk of defaulting on fee payments and enable timely interventions to improve collection rates and financial stability. Shoaib et al. (2024) showed that AI improves credit risk assessments and financial operations in banking; similar models can be adapted to monitor tuition payments. Saúde et al. (2024) and Batista et al. (2024) emphasised that AI can personalise student support and learning pathways to improve graduation rates, thereby strengthening eligibility for performance-based government subsidies. Another promising opportunity lies in applying dynamic pricing strategies to executive education and non-degree programmes. AI-driven analytics can assess market demand, analyse competitor pricing, and recommend optimal fee levels that maximise income per student while maintaining competitiveness. Although research on dynamic pricing within universities remains limited, AI-enabled revenue-management approaches are well established in sectors such as aviation and hospitality. Participants in this research noted that similar techniques could be

adapted to higher education, particularly for pricing short courses and professional training offerings. These applications illustrate how AI can help universities fine tune core revenue streams as well as expand into new markets.

However, implementing dynamic pricing within higher education introduces important ethical and equity considerations. Adjusting tuition or course fees based on students' willingness or ability to pay could unintentionally reinforce existing social inequalities, particularly if wealthier students gain preferential access to programmes or enhanced services. There is little empirical guidance on how universities might implement pricing algorithms without violating principles of equity and affordability. This highlights the need for research that weighs financial gains against the ethical implications of revenue optimisation strategies.

2.6.4 Fundraising and partnerships

GenAI's ability to analyse unstructured data and generate personalised communications can also enhance fundraising and partnerships. Farrelly and Baker (2023) suggested that AI can enhance alumni engagement by generating personalised and targeted communication to strengthen long-term relationships. Although research on AI-enabled fundraising in higher education remains limited, existing findings align with broader principles of data-driven decision-making. Collectively, these insights illustrate how universities can leverage AI technologies to expand "third-stream" income through more strategic and efficient alumni and donor outreach.

2.7 Ethical and critical perspectives on GenAI adoption

Debates surrounding GenAI in higher education extend well beyond cost reduction and revenue generation; they also raise complex ethical, cultural, and academic questions. Scholars have cautioned that AI adoption introduces new risks, particularly in middle-income countries where digital infrastructure and technological literacy remain uneven (Kalniņa, Nīmante, & Baranova, 2024). Research on AI in education identifies several recurring concerns.

These include insufficient teacher expertise and limited technical infrastructure, which can constrain meaningful integration; doubts about cost-effectiveness and whether advanced AI systems justify their expense; and cultural mismatches that arise when tools are designed for contexts different from those in which they are implemented. Additional challenges relate to data protection, privacy, and

cybersecurity, as well as fears that AI may erode human autonomy or facilitate academic misconduct (Kalniņa, Nīmante, & Baranova, 2024).

Ethical debates have intensified with the rise of generative models like ChatGPT, which can produce convincing text and code. Crowe, LaPierre, & Kebritchi (2017) argued that AI tools may facilitate plagiarism and compromise academic integrity. In response, scholars recommend re-designing assessments to emphasise critical thinking and personal reflection, tasks that cannot be easily outsourced to (Kalniņa, Nīmante, & Baranova, 2024). Scholars also emphasise the importance of building AI literacy among both educators and students to ensure that these tools are used responsibly and ethically (Baytas, 2025).

Recent reviews further show that the risks associated with GenAI extend beyond academic integrity to include concerns around fairness, inclusivity, and environmental sustainability. Francis, Jones, and Smith (2025) noted that GenAI systems often reproduce the biases embedded in their predominantly Western-centric training data, which are shaped by contributions from socially and economically privileged groups. If universities adopt such tools without contextual adaptation, they risk reinforcing cultural stereotypes and undermining ongoing efforts to decolonise curricula. The same review highlighted that many advanced AI models operate on subscription-based platforms requiring high-bandwidth internet access; conditions that privilege well-resourced institutions and individuals (Francis, Jones, & Smith, 2025). This dynamic contributes to a widening digital divide, where students and staff without reliable connectivity or sufficient funding are excluded from accessing the most powerful tools. Furthermore, the energy demands of GenAI model training are considerable; the carbon emissions produced in developing large-scale language models raise critical questions about the environmental sustainability of AI adoption (Francis, Jones, & Smith, 2025). These ecological and equity concerns challenge assumptions that AI automatically advances sustainability, reinforcing the need for more responsible and energy-efficient computing practices.

Recognising these multi-dimensional risks highlights that ethical considerations are central (not peripheral) to evaluating GenAI's role in higher education. Beyond issues of integrity, scholars also debate the cultural implications of AI. Because most systems are trained on data from the Global North, they often fail to reflect African languages, worldviews, or epistemologies. Kuleto et al. (2021) argued that financial constraints have prompted several universities to develop low-cost, locally designed

technologies, demonstrating that “one-size-fits-all” approaches are rarely effective. The ethical competence required for AI adoption therefore includes the ability to interpret data responsibly, maintain transparency, and preserve human oversight throughout implementation (Kalniņa, Nīmanīte, & Baranova, 2024).

African commentators similarly advocate for culturally grounded AI ecosystems that incorporate local languages and reflect diverse learning needs rather than relying on imported systems (Sahai, 2025). This aligns with the African Union’s Continental AI Strategy, which calls for data sovereignty, inclusive governance, and context-sensitive innovation (Sahai, 2025). For universities exploring GenAI as a tool for financial sustainability, these debates indicate that adoption must be guided by clear ethical standards, robust data-governance frameworks, and ongoing stakeholder engagement to ensure that technology complements (rather than compromises) core educational values.

Critical perspectives also question whether AI truly delivers cost savings once hidden expenses are considered. Infrastructure upgrades, data-management systems, and recurring licensing fees can offset efficiency gains, while automation may inadvertently displace workers or advantage only those with advanced digital skills. Consequently, comprehensive cost–benefit analyses must extend beyond financial metrics to incorporate social, ethical, and environmental dimensions.

In this research’s context, ethical and financial considerations are deeply interconnected. Universities cannot credibly claim to pursue sustainability if AI adoption perpetuates inequity or erodes trust within their communities. A critical and balanced perspective is therefore essential to weigh GenAI’s potential benefits against its possible harms, ensuring that technological progress supports (not undermines) the transformative mission of higher education.

2.8 Institutional readiness and policy frameworks

The successful adoption of GenAI depends not only on ethical safeguards but also on institutional readiness and supportive policy environments. Insights from India’s higher education sector, summarised in the EY–FICCI “Future-Ready Campuses” report, highlight that effective integration requires embedding AI literacy across disciplines, investing in resilient digital infrastructure, and cultivating collaborative ecosystems to shift from pilot projects to strategic adoption (EY–Parthenon, 2025).

The report further recommends reskilling faculty, redesigning curricula, and strengthening data infrastructure, governance, and policy frameworks to promote fairness, transparency, and accountability (EY-Parthenon, 2025). These recommendations strongly align with conditions in many African contexts, where limited digital infrastructure and skills shortages remain significant barriers to AI implementation.

Similarly, an article published in CIO Africa argued that African countries must move beyond strategy formulation toward implementation by deploying adaptive, data-centric, and culturally grounded AI models (Sahai, 2025). It emphasised that uneven connectivity across the continent necessitates the development of low-bandwidth and offline-capable AI platforms to serve underserved regions effectively (Sahai, 2025). Policy dialogues such as the African Union's Continental AI Strategy also urge member states to institutionalise ethical frameworks, enhance data governance, and foster cross-sector collaboration (Sahai, 2025). Ongoing investment by global technology companies (such as Microsoft's initiative to train one million South Africans in AI and expand national data-centre capacity) demonstrates how public–private partnerships can strengthen the digital ecosystem required for sustainable adoption (Sahai, 2025).

Another crucial dimension of readiness relates to human capital. The Ithaka S+R cross-institutional study revealed that instructors and researchers exhibit wide disparities in their familiarity and comfort with GenAI (Baytas, 2025). Many instructors reported independently experimenting with AI tools in teaching without clear institutional guidance on issues such as academic integrity, ethical standards, or discipline-specific applications (Baytas, 2025). Researchers expressed similar concerns regarding the lack of clear ethical frameworks and limited access to computational resources (Baytas, 2025). To close these gaps, the study recommended coordinated AI-literacy initiatives, top-down policy direction, and equitable access to AI tools and training (Baytas, 2025).

These findings underline that successful GenAI adoption requires not only digital infrastructure but also institutional support structures (governance frameworks, training programmes and communities of practice).

Finally, national and continental policy frameworks establish the broader enabling conditions for AI in education. The African Union's Continental AI Strategy, along

with country-level policies in nations such as Ghana and Rwanda, prioritises privacy protection, algorithmic transparency, bias mitigation, and data sovereignty (Sahai, 2025). However, regulatory clarity in South Africa remains limited, creating uncertainty for institutions seeking to implement AI responsibly. Universities therefore need to engage proactively with policymakers, regulators, and industry partners to co-design standards that safeguard student data, promote equity, and foster innovation. In the absence of such frameworks, AI adoption may become fragmented, inconsistent, and potentially harmful to institutional integrity and public trust. Institutional readiness and supportive policies are thus the bedrock on which GenAI's financial promise will be built.

2.9 Enablers and barriers to GenAI adoption

The benefits of GenAI will remain theoretical unless institutions address critical enablers and barriers. The literature refers to several cross-cutting factors. First, robust digital infrastructure and high-quality data are essential. Kurien and Soglo (2024) pointed out that inadequate digital infrastructure and unreliable data systems hinder AI deployment in African universities. Butcher et al. (2021) noted that outdated information systems and weak data-management capacity continue to obstruct the effective adoption of AI in universities. Similarly, EY-Parthenon (2025) emphasised that sustained investment in digital infrastructure and the strengthening of data-governance frameworks are essential prerequisites for meaningful AI integration across higher-education institutions.

Second, limitations in human capital and digital skills were consistently identified as a major bottleneck to the successful adoption and integration of AI within universities. Butcher et al. (2021) and Kurien and Soglo (2024) documented a shortage of staff with AI and data science expertise in African higher education. EY-Parthenon (2025) underscored the importance of reskilling academic staff and redesigning curricula as critical steps toward building institutional readiness for effective artificial intelligence (AI) adoption. The CIO Africa article described national efforts to train one million South Africans in AI and expand local data centre capacity (Sahai, 2025). In this research, participants consistently emphasised that recruiting and developing AI-literate personnel was essential for effective adoption. Several interviewees described initiatives to establish cross-functional teams that integrate financial, information technology, and academic expertise. They cautioned that without

adequately skilled staff, AI tools could easily be underutilised, misapplied, or misinterpreted, limiting their strategic value and impact.

Third, strong leadership commitment, well-defined strategic direction, and effective governance structures were identified as critical enablers of successful AI adoption. Kurien and Soglo (2024) found that the absence of AI strategies and leadership support created uncertainty and slowed adoption in African universities. EY-Parthenon (2025) similarly emphasised that universities must move from isolated pilots to strategic integration, supported by governance frameworks that ensure fairness, transparency and accountability. Participants in this research observed that universities with clearly articulated digital transformation strategies tended to advance further in adopting AI than those lacking such frameworks. They also expressed concerns about data privacy, ethical use, and algorithmic bias; issues that mirror wider debates on AI governance. Establishing institutional ethical guidelines and ensuring compliance with data-protection legislation were viewed as essential for fostering trust and accountability in the deployment of AI tools.

Fourth, the wider policy and regulatory environment played a pivotal role in shaping the pace and direction of AI adoption within universities. The African Union's Continental AI Strategy and national AI policies emphasised education and encouraged ethical AI frameworks (Sahai, 2025).

However, participants expressed uncertainty about the availability of clear regulatory guidance and emphasised the need for stronger support from government agencies. The literature suggests that underdeveloped regulatory environments can have dual effects; either enabling experimentation or prompting excessive caution in implementation (Sahai, 2025). Public-private partnerships, such as Microsoft's investment in South African data centres, illustrate that effective collaboration among universities, industry, and government will be vital for building the infrastructure, skills, and policy frameworks required to support responsible AI adoption (Sahai, 2025).

Finally, the literature underscores that ethical governance and accountability should not be treated as secondary concerns but as core enablers of sustainable GenAI integration. Francis, Jones, and Smith (2025) argue that robust ethical frameworks are essential for managing the social and academic impacts of GenAI, particularly regarding integrity, equity, and responsible use. They recommend that institutions

embed GenAI literacy programmes across disciplines, redesign assessment practices to foster critical thinking, and implement transparent policies that uphold fairness and accountability (Francis, Jones, & Smith, 2025). Moreover, the environmental cost of AI must also feature in governance discussions. The significant carbon emissions generated in training large models highlight the need for sustainable procurement policies and green-computing strategies (Francis, Jones, & Smith, 2025). By integrating ethical, social, and environmental considerations into strategic planning, universities can prevent unintended harms and strengthen public trust in AI-driven initiatives. This holistic perspective on enablers recognises that the adoption of GenAI extends beyond technical capacity or digital skills; it also depends on institutional values, accountability, and long-term sustainability.

In summary, both the literature and this research's empirical evidence converge on the view that GenAI adoption is a socio-technical effort. Its success depends not only on technological capacity but also on the availability of adequate infrastructure, skilled personnel, strong leadership, effective governance, ethical integrity, and supportive policy environments. Collectively, these enablers and barriers form a conceptual foundation for interpreting the results presented in Chapter 6 and for shaping the recommendations for institutional practice.

2.10 Research gap and contribution

Despite a growing body of research on AI in higher education, no comprehensive research has yet examined how GenAI could specifically address the financial sustainability challenges faced by universities, particularly within the South African context. Existing scholarship has either concentrated on pedagogical or academic applications of AI, explored financial challenges without integrating GenAI considerations, or investigated AI adoption in other sectors without translating those insights to higher education. Moreover, global studies have generally focused on isolated efficiency improvements, often overlooking the structural and systemic nature of financial crises within universities. Research on AI in African higher education, while expanding, has seldom extended its scope to encompass financial management and strategic resource sustainability. The cross-cutting factors identified in the literature also lacked empirical grounding in university finance.

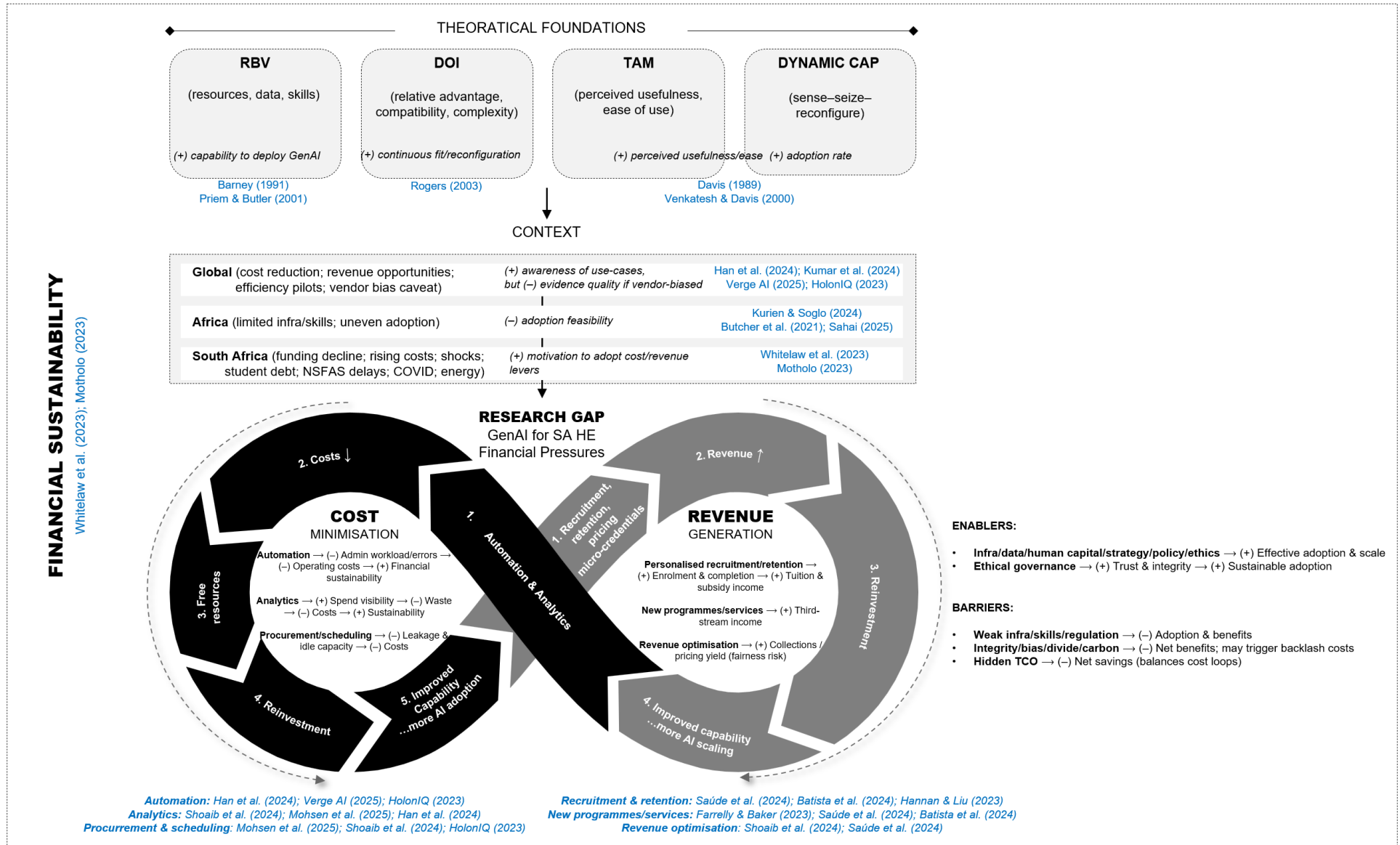
This research was therefore designed to address a significant gap in the existing body of knowledge. By exploring the perspectives of university decision-makers on

how GenAI could both reduce operational costs and enhance revenue generation, it sought to bridge theoretical understanding with real-world application. The research contributes to the literature by integrating AI into the discourse on financial sustainability and by empirically analysing how organisational capabilities, infrastructure, skills, and policy environments shape the impact of GenAI within higher education institutions. The research thus extended higher education management research and the emerging body of work on practical GenAI applications in organisational settings. The findings were expected to guide university leaders and policymakers by identifying feasible applications, highlighting enablers and barriers, and suggesting directions for future research. Importantly, the research emphasised that GenAI should not be regarded as a standalone solution or “silver bullet”, but rather as one component of a broader institutional strategy that integrates cost optimisation with revenue diversification.

2.11 Literature-derived GenAI system dynamics model (integrative synthesis)

Building on what was established in sections 2.1 to 2.10, this section synthesised the literature into an initial integrated systems model. The purpose of this model was to visually map how GenAI interacted with university financial sustainability through reinforcing loops (cost optimisation and revenue generation) and balancing loops (infrastructure, ethical, skills and hidden cost constraints). The system dynamics perspective reflected the consensus in the literature that GenAI is not a linear intervention but a complex socio-technical mechanism whose impact is shaped by institutional capabilities, contextual pressures and feedback effects over time.

This literature-derived model therefore functioned as the conceptual core of the research. It distilled the fragmented academic debates into an initial coherent analytical framework which explained not only whether GenAI affected financial sustainability, but how, under what conditions, and through what reinforcing or constraining mechanisms. In doing so, it set the theoretical logic that guided the following phases of this research.



THEORETICAL FOUNDATIONS

The diagram's top layer brought together key innovation theories that frame GenAI adoption in universities; RBV (Barney, 1991; Priem & Butler, 2001), DOI (Rogers, 2003), and TAM (Davis, 1989; Venkatesh & Davis, 2000). Together, these theories suggested that GenAI adoption required not only cutting-edge tools but also supportive resources, norms and perceptions. A Dynamic capabilities perspective complemented these models by capturing change over time. In rapidly evolving digital environments, universities must "sense, seize and reconfigure" resources to respond to innovation. Applied here, RBV plus dynamic capabilities imply that institutions will benefit from GenAI only if they continuously upgrade data infrastructure, staff skills and routines. In short, theory predicted that GenAI can improve financial outcomes only when aligned with an institution's unique resources and adaptive capabilities.

GLOBAL, AFRICAN AND SOUTH AFRICAN CONTEXTS

Overlaying these theories was the real-world context of higher education finance. Globally, studies note that AI can automate administrative tasks, provide predictive analytics and personalise student services, leading to lower costs and higher revenues. For example, AI chatbots can handle routine inquiries 24/7, reducing staffing needs and freeing funds (Han et al., 2024; Verge AI, 2025). Predictive budgeting tools and personalised marketing can similarly boost tuition income and fundraising, creating virtuous feedback for well-resourced universities.

By contrast, African universities face severe constraints; most lack sufficient funding, networks and infrastructure to support advanced AI. Butcher et al. (2021) and others report that sub-Saharan universities generally cannot finance the high-performance computing, data storage and skilled staff required for GenAI. Ethics and equity concerns further complicated adoption; stakeholders in resource-limited settings worried about bias, academic integrity and data privacy (Patterson et al., 2025). In short, the African context reduced DOI's relative advantage and amplified TAM's perceived difficulty.

South African institutions faced a unique mix of opportunities and pressures. Declining state funding and rising student debt created an urgent need for new revenue streams, making innovative tools attractive. At the same time, many South African universities struggled with decaying infrastructure, electricity outages and underinvestment (Whitelaw et al., 2023; Motholo, 2023). Researchers stress that

without substantial investment in data centres, networks and digital skills, GenAI pilots will remain isolated experiments (Kurien & Sogolo, 2024; Butcher et al., 2021). These regional realities mean that the theoretical promise of GenAI (from RBV, DOI, TAM) must be strengthened by ground-level factors; resource constraints, policy gaps and socio-technical challenges.

REINFORCING FEEDBACK LOOPS: COST MINIMISATION AND REVENUE GENERATION

The diagram identified two reinforcing (positive) feedback loops by which GenAI can improve financial sustainability:

- *Cost minimisation loop.* GenAI-driven automation of routine processes (e.g. student support chatbots, automated grading, predictive maintenance of equipment) led to immediate cost reductions. These savings became new financial resources that universities can re-invest in further AI infrastructure and training (dynamic capability), creating a virtuous cycle. Studies (Han et al., 2024; Verge AI, 2025) highlighted exactly this effect; as AI streamlined operations, administrative and instructional labour costs dropped, which in turn encouraged deeper GenAI integration. Over time, each iteration of automation lowered the marginal cost of services, reinforcing financial gains.
- *Revenue generation loop.* In parallel, GenAI can spur new revenue streams. By analysing data from recruiters and alumni, AI can optimise student recruitment, tuition pricing and fundraising strategies. For example, targeted AI crafted alumni communications can boost donations and “third-stream” income. Similarly, AI-enabled personalised marketing made universities more attractive to prospective students, increasing enrollments and tuition revenue. As Batista et al. (2024) and Saúde et al. (2024) noted, these gains compound; higher revenue allowed reinvestment in R&D and program development, which further differentiated the university’s offerings and attracted more students. In short, the revenue loop proposed that GenAI increased demand (enrollment, grants, donations) while generating data insights to refine strategy, creating upward pressure on total income.

These loops amplify initial gains into larger financial impact over time.

BALANCING FEEDBACK LOOPS: INFRASTRUCTURE, ETHICS AND HIDDEN COSTS

Counterbalancing the above gains were several balancing (negative) feedback loops reflecting real-world constraints:

- *Infrastructure gaps.* Robust data centers, high-speed networks and stable electricity were prerequisites for GenAI. However, many African and some South African universities face chronic infrastructure shortfalls. In systems terms, poor infrastructure is a balancing loop; as AI rollout begins to gain traction, infrastructural bottlenecks triggered inefficiencies that hinder further progress.
- *Ethical and social concerns.* Stakeholder apprehension about AI (data privacy, bias, academic integrity) could also restrain implementation. Patterson et al. (2025) find that the dominant barrier to AI adoption in Southern African education is ethical unease. Faculty and students may resist GenAI tools if they fear cheating or bias, and governments may impose regulations. Each such concern requires building policies, training and safeguards (ethical AI frameworks), which adds time and cost.
- *Hidden costs.* Finally, the diagram accounted for indirect costs that could erode perceived benefits. Advanced AI is not free; training large models consumes energy and hardware, and licensing or cloud costs can be substantial. New expenses for data management, cybersecurity, staff retraining and maintenance create a hidden “tax” on every AI roll-out. In system terms, this is a balancing feedback; apparent savings trigger investment and operational costs that push back against net financial gain. This loop ensures a holistic view; it is not enough that AI can reduce expenditure on one hand if it increases obligations on another.

Together, these balancing loops mean that without sufficient mitigation, anticipated returns will level off. Infrastructure gaps, ethical constraints and hidden expenditures act like brakes that align with the critical perspectives in the literature.

CONVERGENCE

This literature-derived system model operationalised the insights from Sections 2.1 to 2.10 into an integrated analytical visual lens. It demonstrated how GenAI influenced financial sustainability through interacting cost and revenue dynamics, moderated by institutional enablers and constraints.

2.12 Chapter 2 conclusion

This chapter examined both the theoretical and empirical literature on GenAI and its relationship to university financial sustainability. It established that while GenAI offers clear opportunities for cost optimisation and revenue generation, its real-world impact is mediated by contextual factors such as infrastructure readiness, skills availability, institutional strategy, and ethical governance. The review also revealed that financial applications of GenAI within African higher education remain limited, under-researched, and often fragmented.

By synthesising these insights, the chapter developed an initial, literature-derived conceptual model that integrates the multiple forces influencing GenAI adoption and illustrates the dynamic mechanisms through which financial outcomes may emerge. This model serves as the analytical foundation for the research methodology outlined in Chapter 3, which seeks to test and refine these system dynamics within real-world university settings.

CHAPTER 3: RESEARCH QUESTIONS

This chapter outlines the research questions and objectives that underpin the research. These were formulated to examine the dual financial sustainability levers of cost reduction and revenue generation, while addressing both theoretical gaps and practical challenges identified in the preceding literature review. Together, they provide a structured framework for exploring how GenAI can be applied in ways that are contextually relevant, strategically impactful, and operationally feasible within South African universities.

3.1 Primary research question

The primary research question serves as the central anchor of this research, linking the overarching problem of financial unsustainability in higher education with the emerging technological opportunity presented by GenAI:

Primary Research Question (RQ):

How can generative AI be leveraged to improve the financial sustainability of South African public universities?

This question is grounded in the recognition that GenAI, as a general-purpose technology, possesses the potential to fundamentally transform value creation, cost structures, and operational models within the higher education sector (Renkema & Tursunbayeva, 2024). It acknowledges financial sustainability as a multidimensional construct that encompasses expenditure optimisation, revenue diversification, productivity enhancement, and strategic resilience.

3.2 Research sub-question 1: Operational cost efficiency

South African universities are under mounting pressure to reduce operational expenditures while maintaining quality and access. Administrative functions such as finance, human resources, student administration, and procurement consume substantial resources and are often characterised by inefficiencies, duplication of effort, and manual processes. GenAI offers opportunities to automate routine administrative processes, enhance decision-making through predictive analytics, reduce staff workload, and optimise resource allocation (Shoaib et al., 2024; Knisely & Pavliscsak, 2023). International studies further indicate that AI-driven automation can generate substantial reductions in university operating costs by improving

workflow efficiency, minimising human error, and enhancing the precision of financial and operational management (Hannan & Liu, 2023).

In this context, the first sub-question examines the application of GenAI as a cost-saving mechanism:

RQ1 (cost management):

How can GenAI be used to reduce operational costs and improve efficiency in South African universities?

(Shoaib et al., 2024; Knisely & Pavliscsak, 2023; Renkema & Tursunbayeva, 2024)

This question connects to the theoretical proposition that digital transformation enhances organisational efficiency, while also addressing the practical challenge of escalating operational costs in higher education. It guides the research toward identifying and analysing specific use cases where GenAI can materially reduce expenditure and improve institutional productivity.

Research objective 1: To identify and evaluate the ways in which GenAI applications can streamline processes, optimise resource allocation, or otherwise cut costs in the university context.

3.3 Research sub-question 2: Revenue diversification and growth

While cost efficiency is essential, it alone is insufficient to achieve financial sustainability. South African public universities must also diversify and expand their revenue streams to remain competitive and financially resilient within an increasingly globalised and digitally driven higher education landscape (Farrelly & Baker, 2023). GenAI offers potential to enhance revenue through improved student recruitment and retention analytics, the development of new online and micro-credential programmes, personalised marketing strategies, industry partnerships, and monetisable intellectual property generation (Lin & Yu, 2023; Ebadi, Tremblay, Goutte, & Schiffauerova, 2020). Moreover, AI-based tools can support universities in expanding lifelong learning offerings and capturing new market segments, thereby increasing third-stream income.

To explore these opportunities, the second sub-question focuses on GenAI's potential to enhance institutional income:

RQ2 (revenue generation):

How can GenAI be used to enhance revenue generation for South African universities?

(Hannan & Liu, 2023; Shoaib et al., 2024; Ebadi et al., 2020; Farrelly & Baker, 2023; Lin & Yu, 2023; University B, 2022)

This question responds to theoretical work on strategic innovation and digital entrepreneurship in higher education, as well as to the practical need for universities to expand self-generated income amid declining state subsidies (Motholo, 2023). By examining how GenAI can unlock new and diversified revenue pathways, this research contributes to the broader understanding of technology-enabled financial sustainability while offering actionable insights for university leadership.

Research objective 2: To identify and evaluate the ways in which GenAI applications can contribute to increasing or diversifying university revenues.

3.4 Chapter 3 conclusion

This chapter has outlined the research questions and objectives that underpin the research. By addressing both cost reduction and revenue generation, these questions establish a comprehensive framework for examining how GenAI can be strategically adopted to strengthen the financial sustainability of South African public universities. The research questions integrate theoretical relevance with practical urgency, and the associated objectives provide clear direction for the methodological approach that follows in Chapter 4.

CHAPTER 4: RESEARCH METHODOLOGY

This chapter explains how the research answered the main question; *How can generative AI be leveraged to improve the financial sustainability of South African public universities?* It explains the logical reasoning behind the research, the selection of cases and participants, the processes used for data collection and analysis, and the measures adopted to ensure quality and ethical integrity.

4.1 Research philosophy and approach

4.1.1 Philosophical stance

The research took an interpretivist view of reality and knowledge. Interpretivism says that social reality is made by people's meanings and that researchers and participants create knowledge together. Saunders et al. (2003) explain that this view looks at how culture and context shape what people think. This view suited the research because GenAI is not neutral; leaders, finance managers and technologists may see it differently. It allowed the researcher to learn how participants understood AI in their universities and to recognise that the researcher's own experiences also mattered.

4.1.2 Research approach

The research used an inductive approach. Saunders' (2003) research onion shows that researchers can test existing theory (deductive) or build theory from data (inductive). GenAI in higher education finance is new and lacks theory, so building from data was more suitable. The research aimed to develop insights from what participants said rather than to test fixed ideas. The research questions guided data collection, but they did not dictate the results. This inductive process fits an exploratory case study and reflects the interpretivist focus on context and meaning.

4.2 Research design

4.2.1 Choice of research strategy and time horizon

The research used a qualitative multiple case study. Yin (2017) notes that case studies are good for "how" or "why" questions about current issues when researchers cannot control events. AI adoption in universities fits this definition because it is new and complex and the researcher could not control it. A single case might give results that apply only to one university; a multiple case allowed comparison and broader

insights (Roller & Lavrakas, 2015). Roller and Lavrakas (2015), drawing on Stake (1995), distinguish among three types of case studies: intrinsic, instrumental, and collective. This research employed both an instrumental and collective design, as each institutional case was examined to gain a deeper understanding of the broader challenge of financial sustainability within South African universities. Data were collected between August and September 2025, providing a contemporary snapshot of prevailing practices and institutional experiences. A longitudinal study was not possible due to time limits and rapid technology change.

4.2.2 Justification for qualitative methodology

Qualitative methods were chosen because they are better for exploring new or complex issues than quantitative methods. GenAI adoption involves organisational culture, leadership views, risk tolerance and resources. Because these factors are nuanced and shaped by institutional context, interviews were deemed more suitable than surveys. The qualitative approach enabled the researcher to explore rich, in-depth accounts of experiences, perceptions, and contextual dynamics that would be difficult to capture through quantitative methods.

4.3 Population and unit of analysis

4.3.1 Population

The population was the 4 of the 26 public universities in South Africa. Public universities share legislative and funding frameworks but differ in size, mission, location and resources. Private universities and technical colleges were not included because they have different contexts. The research selected a sample of cases to reflect diversity in financial health and AI adoption.

4.3.2 Unit of analysis

It is important to define what is being studied (Roller & Lavrakas, 2015). In this research the unit of analysis was each of the 4 universities and their unique decision-making processes. Data were collected from different people in each university to understand how financial and technology strategies worked together. Interviews with finance leaders (Chief Financial Officers (CFOs) and Finance Directors) explained budgets and cost management; interviews with information technology leaders (Chief Information Officer (CIO) and IT Directors) explained AI implementation; interviews with security leaders (Chief Information Security Officer (CISO)) provided

insights into cybersecurity risks and governance related to AI adoption; and a Higher Education Finance Subject Matter Expert (SME) provided sector-level insights into financial pressures and sustainability trends across universities. This organisational and SME focus allowed comparison across cases while recognising the role of individuals.

4.4 Sampling method and sample size

4.4.1 Case selection

The research used purposeful sampling. This approach involved selecting cases that offered rich and relevant insights aligned with the research questions. Four universities were purposefully chosen based on their classification (Tier 1 versus Tier 2), financial status, engagement with GenAI, and willingness to participate. This diversity enabled meaningful comparison across institutions and facilitated the exploration of different approaches to AI adoption and financial management (Roller & Lavrakas, 2015).

4.4.2 Participant selection

The research employed purposive sampling to intentionally select individuals occupying strategic roles within public universities who are directly engaged in financial decision-making, digital transformation, and technology governance. In qualitative research, purposive sampling is particularly suitable when the aim is to gather insights from participants with specialised expertise and firsthand understanding of the topic under investigation. In this case, the participants were the most senior leaders responsible for decisions on budgets, cost optimisation, revenue generation, information systems and cybersecurity; all areas which directly influence the adoption and financial impact of GenAI in universities.

A total of nine senior executives were interviewed across multiple public universities. These included those in the roles of CFOs, CIOs, CISO, finance executive directors, digital or information technology directors, as well as finance subject matter expert in higher education. These roles were selected because they influence and oversee the strategic direction of both financial sustainability and digital innovation within their respective institutions. The participants were directly responsible for approving or rejecting technology investments, monitoring financial performance, and managing institutional risks; including cybersecurity threats associated with AI-enabled

systems. Their perspectives offered valuable insights into the opportunities and constraints shaping GenAI adoption in South African universities.

Participants were invited via email, which included an information sheet outlining the purpose of the research, their rights as participants, and the measures taken to ensure confidentiality and ethical compliance. A consent form accompanied each invitation and was signed before interviews commenced. The interviews were scheduled at times chosen by the participants to minimise disruption to their work schedules.

In addition to purposive sampling, the research used snowball sampling to reach additional relevant decision-makers. This approach is widely applied in qualitative research to identify individuals who may not appear prominently in formal organisational charts but are recognised by their peers as key contributors to institutional technology and financial strategies. Some participants recommended colleagues who were either leading internal AI initiatives or were directly affected by them, particularly in finance or technology departments. This approach ensured that the sample captured a balanced range of institutional perspectives on GenAI, spanning both strategic and operational domains.

The final sample size of nine participants is appropriate for this research because the number of individuals holding these executive roles in each university is limited. These are specialised leadership positions that typically exist as single appointments at executive level, rather than large departments. As a result, the sample reflects near-complete coverage of the available population of decision-makers responsible for the financial and technological adoption of GenAI in the sector. This approach strengthened the credibility of the findings by grounding them in the perspectives of individuals with the authority and insight to influence financial sustainability and digital transformation within South African universities.

4.4.3 Sample size justification

Qualitative research is designed to obtain deep insight from a focused group of knowledgeable participants rather than from a large sample. Scholars such as Yin (2017) and Saunders et al. (2018) emphasise that when the unit of analysis involves institutional decision-making, it is most appropriate to purposefully select participants who possess both the authority and contextual insight necessary to engage meaningfully with the phenomenon under study. In this research, nine senior

executives were interviewed across finance, technology and cybersecurity portfolios. These roles were selected because they are directly responsible for financial strategy, digital investment and operational sustainability in their institutions, which makes them information-rich cases (Palinkas, Horwitz, Green, Wisdom, Duan, & Hoagwood, 2015).

Academic guidance confirms that qualitative studies typically reach thematic saturation with between 6 and 12 interviews when participants occupy similar positions of expertise and operate within a defined context (Guest, Namey & Chen, 2020). Saturation is reached when new interviews no longer produce novel insights (Saunders, Sim, Kingstone, Baker, Waterfield, Bartlam, & Jinks, 2018). In this research, no new ideas emerged after the seventh interview, and themes began to repeat consistently across institutions. This confirms that saturation was achieved, and further interviews were unlikely to change the findings. Yin (2017) argues that in case study research, the goal is not statistical generalisation, but analytical generalisation, where findings are transferable to similar settings based on logic and applicability. Because participants were drawn from multiple universities and represented a range of strategic roles, the research produced credible and contextually grounded insights that reflect broader dynamics within the higher education sector.

Although the sample size is modest in statistical terms, it is methodologically appropriate for qualitative case research that prioritises depth, context, and meaning. The inclusion of multiple institutions and diverse strategic roles supports triangulation and strengthens the credibility of the findings. Accordingly, the sample of nine participants is justified, defensible, and aligned with established standards for qualitative inquiry.

4.5 Data collection

4.5.1 Measurement instruments

Data were collected through semi structured interviews (conducted using a detailed interview guide developed based on the literature review and aligned with the research questions; the full interview protocol, including sections, prompts, and probes, is provided in Appendix A), and document analysis (documents reviewed included universities' strategic plans and annual reports).

4.5.2 Data gathering process

Data were collected primarily through semi-structured interviews with senior leaders from South African public universities. The interviews took place over a six-week period between August and September 2025. All sessions were conducted virtually via secure online meeting platforms, which provided flexibility for participants based in different provinces and accommodated their demanding executive schedules. The online format also mirrored the increasing normalisation of digital engagements within the higher education sector and facilitated a consistent, efficient data collection process.

Each interview lasted between 45 and 60 minutes, depending on the participant's role and level of involvement in GenAI-related initiatives. Before each interview, participants were provided with an information sheet explaining the purpose of the research, what participation would involve, and ethical assurances such as confidentiality and voluntary participation. Formal consent was obtained prior to data collection.

A semi-structured interview guide was used to direct the conversation. This guide contained open-ended questions linked to the research objectives, but it also allowed flexibility for participants to elaborate on their experiences, provide institutional examples, and raise issues that were not anticipated in advance. This approach ensured that the interviews remained anchored to the research questions while allowing participants the flexibility to share insights drawn from their expertise and lived institutional realities.

With permission from participants, all interviews were audio recorded in order to capture the data accurately. Recording the interviews ensured that no information was lost and allowed the researcher to revisit the conversations in full. Immediately after each interview, the recordings were transcribed into written text to prepare them for later stages of analysis.

In addition to interviews, relevant documents were gathered from publicly available sources such as institutional websites, annual reports, strategic plans and digital transformation plans. These documents were not analysed at this stage but were collected to provide contextual background to support understanding of the institutional environment in which participants operated. The gathering of multiple types of data ensured that the research was informed by both spoken evidence

(interviews) and documentary evidence, consistent with qualitative research best practice.

4.6 Data analysis

4.6.1 Analytical framework

The research used reflexive thematic analysis. Byrne (2022) states that Braun and Clarke describe thematic analysis as a method where the researcher actively creates themes rather than simply finding them. Recent guides stress that the researcher plays an active role and that the process is iterative, moving back and forth between stages (Byrne, 2022). The analysis followed six phases: “getting familiar with the data, coding, generating themes, reviewing and refining themes, defining and naming themes, and writing up”.

To ensure internal coherence and methodological rigour, a consistency matrix was developed (see Appendix B), which mapped each research question to the supporting literature, corresponding interview questions and the thematic analysis plan. This alignment ensured that data collection and analysis were directly guided by the theoretical foundations and objectives of the research.

4.6.2 Step by step analytical procedure

Analysis was done manually using Microsoft Excel. Each transcript was placed in an Excel sheet with columns for line numbers, text, codes, theme categories and memo notes on the transcripts. Colour coding and filters helped organise the data. The steps were:

a. *Familiarisation*: Memo notes were added to the interview transcripts to clarify ambiguous passages, capture non-verbal cues, and record preliminary analytical reflections. This process of cleaning and annotation ensured that the data were accurate, well-organised, and ready for systematic coding.

b. *Initial coding*: Each significant statement was then coded within an Excel sheet to begin identifying recurring concepts and patterns across participants. Codes described actions and meanings. Inductive codes (from the data) were used. Codes were kept descriptive at this stage.

c. *Generating initial themes*: Codes were grouped into preliminary themes, beginning with an initial set of twenty-five. These early themes captured broad patterns

emerging from the data and served as the foundation for subsequent refinement and consolidation. These were further refined and consolidated, for example, codes about automation to reduce labour/operational costs, cutting non-essential expenditures and data-driven budgeting and cost management formed the theme “AI-driven cost savings”. Codes about automating administrative processes, enhancing decision-making with analytics and streamlining academic and support workflows formed “AI-Driven Operational Efficiency Gains”. Grouping was iterative and used the memo notes.

d. *Reviewing and refining themes*: Themes were checked against the data and refined. Some themes were divided into subthemes or merged. Excel helped establish relationships between themes and codes.

e. *Defining and naming themes*: Themes were clearly defined and named. Rationale summarised on what each theme revealed about the role of GenAI in cost management and revenue generation. Mapping was also conducted to illustrate how the themes interconnected with one another and how each aligned to the corresponding research questions.

f. *Writing up*: The final stage involved developing the analytical narrative. Participant quotes were carefully selected to illustrate key themes and ensure that their voices were authentically represented within the findings. The write up linked themes to theoretical propositions and literature. Writing and analysis informed each other until the narrative was complete.

4.6.3 Use of software

Excel was used for all stages of data organisation and analysis. It allowed the researcher to arrange transcripts, codes, and themes in a structured way, use colour coding, and merge related narratives. Although specialised software such as NVivo or MAXQDA provides advanced analytical capabilities, the use of Excel was considered sufficient for the research’s relatively small dataset and offered a transparent and easily auditable coding process.

4.7 Quality controls and trustworthiness

4.7.1 Credibility

Credibility concerns the extent to which the study’s findings are believable and accurately represent participants’ perspectives. To strengthen credibility, the

researcher engaged deeply with participants and employed triangulation, comparing insights across multiple interviews as well as with relevant institutional documents. In addition, the research supervisor independently reviewed the coding and emerging themes to validate the interpretation and ensure analytical consistency.

4.7.2 Transferability

Transferability concerns whether findings can apply to other contexts. The research offered detailed descriptions of each participating university, outlining the roles of participants, the nature of their AI initiatives, and the broader financial contexts in which these projects were situated. The sampling included diverse cases to show variation (tier 1 vs tier 2 universities). Later chapters discuss context so that readers can judge whether the findings apply to their own situations.

4.7.3 Dependability

Dependability means the research process is consistent. An audit trail recorded all methodological decisions, interview guide changes, coding schemes, theme development and memo notes. Different versions of the documentation (from Excel to word) were saved after each coding session, with dates to track changes. Notes were kept in the transcripts and in separate documents. Memo notes captured the researcher's thoughts and decisions as part of commentary on the transcripts.

4.7.4 Confirmability

Confirmability means the findings reflect participants' views rather than the researcher's bias. Comparing an interview with other interviews ensured that themes were grounded in participants' narratives. The supervisor reviewed the audit trail, coding and themes to ensure they were based on data.

4.8 Research ethics

Ethical approval was obtained from the university's leadership before data collection. Participants were given an information sheet explaining the research and signed consent forms before being interviewed. Participation was voluntary; participants could withdraw at any time without consequences, and no incentives were offered. Confidentiality was protected by using pseudonyms and storing data securely. Interviews were private. When reporting findings the researcher used general terms

and anonymised quotes to minimise harm. Data handling complied with the Protection of Personal Information Act.

4.9 Limitations and delimitations

The research's scope and design presented several limitations, but deliberate steps were taken to minimise their impact. Only four universities and nine participants were included, which limits the representativeness of the findings. To address this, participants were purposively selected from different institutional types and roles (finance, technology, and governance) to ensure diverse perspectives. Although the sample size was small, it allowed for depth of engagement and deep exploration of context.

The cross-sectional design captured insights at a specific point in time, even though both GenAI technologies and university financial conditions evolve rapidly. This was mitigated by including up-to-date institutional reports and national policy documents to complement interview data, ensuring that interpretations reflected current realities rather than isolated viewpoints.

Because the study relied primarily on participants' accounts, the findings may contain some bias or subjective interpretation. To strengthen credibility, the researcher triangulated interview data with institutional documents, industry reports, and recent academic literature. Emerging themes were validated through pattern checking across multiple participants and compared with existing theory to confirm consistency.

Finally, as an interpretivist study, the findings are understood as co-constructed between the researcher and participants, representing shared meaning rather than objective truth. The research deliberately focused on public universities and GenAI applications related to financial sustainability, excluding teaching, learning, or student support systems. The conclusions should therefore be interpreted within this clearly defined context and scope.

4.10 Chapter 4 conclusion

This chapter outlined the methodological approach used to investigate how GenAI can enhance financial sustainability within South African public universities. The research adopted an interpretivist and inductive orientation, employing a qualitative multiple-case design. Cases were selected purposefully, and in-depth interviews

were conducted with nine senior university leaders occupying strategic roles across finance, technology, and institutional management. Data were collected through semi structured interviews and document analysis, then analysed with reflexive thematic analysis using Excel. Quality controls ensured the trustworthiness of the findings, and ethical procedures were followed. While the research has limitations, the methodology was appropriate for the research questions and provides a sound basis for interpreting the results.

CHAPTER 5: FINDINGS

This chapter presents the empirical findings that emerged from the qualitative analysis of interviews and is structured to directly address the research questions guiding the research. The purpose of this chapter is to present the results as stated by participants, organised into themes and sub-themes, without interpretation or theoretical commentary, which will follow in Chapter 6. The findings are presented in relation to the two research questions: (1) How can generative artificial intelligence support cost reduction and improve operational efficiency in universities? and (2) How can generative artificial intelligence facilitate revenue generation and diversification within universities? The findings are then followed by a third section capturing cross-cutting factors that shape the success or failure of these AI initiatives across both dimensions. Together these themes reflect how participants perceive the financial role of GenAI in South African universities.

The data underpinning these findings were derived from nine in-depth interviews with senior decision-makers responsible for financial, technology and cybersecurity. These individuals were purposely selected based on their roles in influencing financial sustainability decisions, making the sample appropriate for answering the research questions. Participants included roles of CFO, CIO, CISO, finance executive director, and information technology/digital leaders, offering a multi-perspective view across finance, technology, and cybersecurity. This strengthens the credibility and relevance of the findings, as the sample comprised individuals with direct responsibility for institutional budgets and technology adoption within their universities.

The interview data were analysed using thematic analysis. Microsoft Excel was used to systematically code the transcripts, organise data extracts into meaning units, and group similar concepts. Codes were refined iteratively to identify recurring patterns across participants. Only themes that were supported by multiple interviewees and directly aligned with the financial focus of the research were elevated to the level of formal findings. To enhance reliability and validity, the coding process involved iterative comparison across interviews to ensure consistency in theme development and to minimise subjective bias. Outlier statements were carefully reviewed to ensure that minority perspectives were not disregarded, while the diversity of participant roles provided a natural form of triangulation across institutional viewpoints.

To further strengthen credibility, interpretive bias was reduced through continuous comparison of data across interviews and through maintaining an audit trail of coding decisions. Divergent perspectives were retained to preserve nuance, while triangulation across roles and institutional documents served as additional verification.

The presentation of findings is organised thematically and structured around the study's research objectives. The first section presents themes relating to cost reduction and efficiency gains, showing how participants believe generative artificial intelligence could reduce expenditure or improve resource optimisation. The second section presents revenue-related themes, explaining how AI could contribute to income generation and diversification. The third section presents factors that influence the implementation and effectiveness of these initiatives across both domains. Verbatim quotations are integrated throughout this chapter to preserve the authenticity of participant voices and to demonstrate that the thematic analysis was firmly grounded in empirical data. Each quotation is accompanied by a concise explanatory narrative that clarifies how the theme connects to the specific research question it addresses. The broader interpretation of these findings, along with their alignment to the existing literature, is presented in Chapter 6.

5.1 Findings related to RQ1: cost management and efficiency

The first research question examined how GenAI can contribute to cost reduction and efficiency improvement within South African universities. Interview data revealed that senior university leaders view GenAI as a practical enabler for managing operational costs, streamlining administrative processes, and enhancing overall productivity. Their perspectives illustrate a growing recognition that AI is not merely a technological innovation but a strategic tool for achieving greater financial efficiency in resource-constrained environments. Through inductive coding of the nine interviews, two overarching themes and several sub-themes were identified. The two major themes are AI-Driven Cost Savings and AI-Driven Operational Efficiency Gains. These themes together illustrate how GenAI is seen as a means to "do more with less" (Kumar et al. ,2024), enabling universities to maintain or improve service levels while managing their cost bases. This section presents each theme in detail, with supporting sub-themes and illustrative quotations from participants. Analytical commentary is kept brief and confined to indicating how each finding answers RQ1.

5.1.1 THEME 1: AI-DRIVEN COST SAVINGS

University finance officers and other senior stakeholders repeatedly highlighted ways in which generative artificial intelligence can help reduce or avoid expenditure. The AI-driven cost savings theme captures initiatives that focus on direct cost optimisation. Three interrelated sub-themes emerged: automation to reduce labour and operational costs, analytics to identify and cut non-essential spending, and data-driven budgeting and cost control. Each sub-theme is presented with participant quotes to demonstrate how artificial intelligence is currently being used or envisioned to reduce costs.

Sub-theme: Automation to reduce labour and operational costs

Participants commonly described the potential for artificial intelligence to automate routine administrative and operational tasks, thereby reducing staff costs and external procurement. One CFO explained that automating repetitive processes would allow existing staff to be redeployed: “If we’re able to use AI to assist with the repetitive processes, we can redeploy the people in those roles to more important areas”. This sentiment reflects a broader view that automation enables institutions to reallocate human resources to higher-value activities without increasing headcount. Another higher ed finance subject matter expert underscored this point, noting that automation can substitute for expensive external consultants: “You can use AI rather than bringing in consultants... you’re able to reduce consultancy costs using the AI”. AI tools that can match invoices to purchase orders, conduct initial screening of job applications, or perform basic data entry were cited as examples of automation that can lower salary overheads or outsourcing fees.

The cost savings from automation are not limited to direct labour. University leaders also mentioned reductions in overtime expenses, temporary staff, and contract labour. Routine administrative task (such as generating reports, sending reminders, or verifying compliance) were frequently described as high-volume activities that could be delegated to automated systems. By performing these functions quickly and consistently, GenAI significantly reduces the number of staff hours required for manual processing. One participant illustrated this potential by describing an AI pilot that processed thousands of student forms within a single hour; a task that would otherwise have taken several days of staff effort. This kind of automation not only reduces labour costs but also improves turnaround times, indirectly enhancing the student experience by reducing waiting periods for administrative responses.

In some cases, automation also reduces costs associated with procurement or external services. For example, participants noted that automated document processing and smart scheduling systems can reduce reliance on manual data entry services or scheduling software licenses. By integrating these functions into their own AI tools, universities save on subscription fees and consultancy charges. A finance manager mentioned that automation allowed their institution to handle invoice reconciliation internally rather than paying a third party: “We had a module that cross-checks invoices with purchase orders automatically; it cut down on the need for external auditors to do that for us”. In these examples, automation is not only about replacing labour but also about consolidating processes and eliminating redundant expenditures.

Sub-theme: Analytics to identify and cut non-essential spending

Beyond automating repetitive tasks, participants emphasised the use of artificial intelligence analytics to monitor and rationalise spending. AI-enabled analysis of financial transactions can reveal patterns, spot anomalies, and highlight waste. One senior finance manager described how GenAI assists in identifying and trimming “fat areas” within university budgets:

“AI can reveal patterns in our spending and highlight high-cost areas, like too much money going to catering or travel, so we can trim those fat areas”.

This analytical capability allows finance teams to detect irregular or inefficient spending that might otherwise remain hidden, such as excessive travel allowances, underutilised facilities, or outdated vendor contracts. By identifying these anomalies early, institutions can reallocate or reduce expenditure without compromising their core academic and operational functions.

Participants provided specific examples of how AI analytics have led to cost reduction. One institution used AI to analyse facility usage and discovered that several buildings were underutilised. By consolidating activities into fewer spaces and closing redundant facilities, one university was able to reduce expenditure on maintenance, security, and utilities. Another CFO explained that GenAI tools had flagged procurement categories that consistently exceeded budgeted thresholds, prompting a review of vendor contracts. Following renegotiations, the institution secured more favourable terms and achieved measurable savings. Similarly, a

finance officer described how AI highlighted excessive spending on catering at institutional events:

“We realised we were overspending on catering; the data showed us that cutting back there wouldn’t affect our operations”.

These examples collectively demonstrate how AI-generated insights enable universities to identify non-essential expenditures, rationalise procurement, and implement targeted cost reductions that preserve essential teaching and research functions.

AI-driven analytics also strengthen expense control by enabling real-time monitoring of transactions. Several participants observed that AI systems can track procurement activities as they occur, immediately flagging deviations from approved policies or thresholds before they result in overspending. One interviewee explained:

“In procurement, AI gives us a great opportunity; it can see the spend patterns and flag where we have deviations from our policies, so we can correct issues before they cost us”.

This proactive capability prevents minor discrepancies from escalating into significant budget overruns. User-friendly AI dashboards that visualise spending patterns in real time further empower finance teams to take corrective action promptly, ensuring that expenditure remains aligned with institutional budgets and compliance requirements.

Sub-theme: Data-driven budgeting and cost control

A third sub-theme within AI-enabled cost reduction concerns the application of AI-powered analytics and forecasting tools in budgeting and financial control. Participants emphasised that AI not only accelerates the budgeting process but also enhances the precision and responsiveness of cost management. One CFO highlighted the time efficiency gained through automation:

“My team spends lots of time on budgets, but by deploying AI tools we could do it just like that. You inform the AI what you need, and it quickly projects our figures”.

By automating the projection of future income and expenditure based on historical data and current trends, AI frees finance teams to focus on strategic decision-making rather than manual calculations. In addition to saving time, participants noted that AI-

generated forecasts enable earlier identification of budget variances, allowing corrective measures before deficits arise. Advanced AI tools can simulate the financial impact of multiple scenarios (such as fluctuations in student enrolment or changes in government funding) thereby strengthening institutional resilience.

One finance executive illustrated this further:

“AI systems can continuously monitor financial transactions to prevent cost overruns or fraud”.

By automatically checking transactions against predefined rules, AI helps reduce the risk of fraud, strengthens compliance, and ensures that expenditure remains within authorised limits.

Finally, participants observed that AI-driven budgeting improves transparency and collaboration across departments. Data-driven reports generated by AI provide clear justification for budget allocations and cost adjustments, fostering shared accountability among academic and administrative units. This enhanced visibility encourages evidence-based dialogue about financial priorities, promoting a culture of fiscal responsibility across the institution. In this way, AI supports not only the technical aspects of budgeting but also the organisational process of setting and communicating financial expectations.

Interpretation of AI-Driven Cost Savings: Across these sub-themes, the findings demonstrate that university leaders view generative artificial intelligence as a tool for immediate financial relief. Automation reduces labour costs and eliminates the need for certain external services; analytics identify and cut wasteful spending; and AI-powered budgeting improves financial control. These initiatives are particularly significant in an environment where university expenditures (especially salaries, utilities, and essential services) continue to rise faster than institutional revenues. By enabling operational efficiencies without compromising quality, AI interventions allow universities to reallocate saved resources toward their core academic mandates or to strengthen their financial resilience. The findings therefore address RQ1, demonstrating that cost containment, as a foundational element of financial sustainability, can be effectively supported through targeted AI applications that streamline operations, enhance oversight, and improve decision-making across functional areas.

5.1.2 THEME 2: AI-DRIVEN OPERATIONAL EFFICIENCY GAINS

The second major theme under RQ1 focuses on the role of artificial intelligence in improving productivity and the quality of services. While cost-saving initiatives emphasise reducing expenditure, efficiency-focused interventions enable universities to achieve greater output and value using the same or fewer resources. In this way, AI contributes not only to cost containment but also to productivity enhancement, laying the groundwork for revenue growth and long-term financial sustainability. Three sub-themes emerged: automating administrative processes, enhancing decision-making with analytics, and streamlining academic and support workflows. These sub-themes reveal the multiple dimensions through which AI is perceived to enhance operational efficiency, thereby strengthening the financial sustainability of universities.

Sub-theme: Automating administrative processes

Participants were unanimous in their belief that AI can simplify and accelerate a wide range of administrative tasks. Admissions filtering, course scheduling, processing paperwork, and answering standard enquiries were all cited as candidates for automation. One CFO observed that AI could automate front-end administrative processes such as the initial screening of student applications and the scheduling of classes:

“AI could handle our initial student admissions screening and even do class scheduling automatically”.

By assigning these repetitive tasks to AI systems, staff are able to concentrate on exceptions and complex cases, thereby reducing manual workload and improving accuracy.

Interviewees also described several successful automation pilots. A finance manager explained that one system processed nearly ten thousand handwritten student forms within an hour, a task that had previously required several days of staff effort. This significant increase in processing speed not only reduced labour costs but also improved service responsiveness, enabling students to receive quicker admissions decisions and communication. Similarly, an information technology director described the deployment of AI-powered chatbots for the student IT helpdesk: “We set up a chatbot for the student IT help... it answers common queries instantly and it freed my team to focus on the tough problems”. Chatbots and self-service portals

reduce the volume of routine enquiries that staff must handle, thereby improving efficiency.

Automated scheduling emerged as another area of significant potential. Participants explained that AI-driven scheduling tools can account for multiple constraints (such as lecturer availability, room capacity, and student enrolment) to generate optimal timetables. These systems can produce complete schedules within minutes rather than weeks, which is particularly valuable for universities with complex academic structures. One finance executive reflected on this shift, noting that their institution previously outsourced class scheduling to external service providers but was now exploring in-house AI solutions:

“The AI can create a timetable in minutes, and we just adjust where necessary; it’s much faster than outsourcing”.

By automating scheduling, universities reduce dependence on external vendors, shorten planning cycles, and improve the utilisation of teaching spaces and staff time.

Sub-theme: Enhancing decision-making with analytics

Another sub-theme focuses on how AI analytics improve the quality and speed of decision-making. Participants emphasised that AI tools can analyse large datasets much faster than human analysts, providing timely insights that support better decisions. Several finance officers reported using AI-powered dashboards to monitor expenditures and cash flow in real time. One CFO shared:

“We now have an AI-powered dashboard watching our finances; it flags irregular expenditures or cash flow issues in real time, so we can respond immediately”.

This immediate feedback enables finance teams to identify and address potential issues before they escalate, improving financial control and responsiveness.

Beyond financial management, AI analytics are also being applied in academic operations to support early identification of students at risk of failure or dropout. An Information Technology Director explained:

“AI highlights students likely to struggle, so advisors can intervene early – we’re preventing problems instead of reacting late”.

By predicting which students may require additional support, universities can intervene proactively to improve retention rates and mitigate the financial losses associated with student attrition, since withdrawals directly affect tuition and government subsidy income. Predictive analytics also inform resource planning, with forecasting models used to estimate future enrolment trends and course demand. This allows institutions to allocate teaching staff and facilities more efficiently, optimising both educational and financial outcomes.

Participants also mentioned the use of AI to generate key performance indicators and performance reports. By automating the collection and analysis of metrics such as teaching loads, research outputs, and resource utilisation, AI allows administrators to monitor performance more effectively. One finance manager commented that they no longer need to manually consolidate data from multiple systems because AI does it automatically: “The dashboard is updated automatically; we don’t chase data anymore”. Such decision-support tools reduce the administrative burden on staff and enable more informed strategic decisions.

Sub-theme: Streamlining academic and support workflows

The final sub-theme relates to the use of AI in academic and support functions. Participants observed that GenAI supports a wide range of knowledge-intensive tasks, including drafting and summarising content, analysing large document sets, and assisting with research and policy development. An information and communication technology director described how lecturers use GenAI to create initial drafts of course material: “Our lecturers started using a GenAI to draft course reading summaries... something that took them hours each week now takes minutes to fine tune”. This automation reduces preparation time, enabling faculty to focus more on teaching or research.

Administrative units also benefit from AI-assisted drafting and analysis. A finance executive reported that an AI tool helps draft policy documents and summarise lengthy contracts: “It’s not perfect, but it gives us a first draft in seconds, and then we just polish it – it saved us so much time on policy reviews”. By speeding up the creation of documents, AI reduces the workload of administrative staff and allows quicker turnaround on important tasks such as policy updates, contract negotiations, and compliance reports. Participants acknowledged that while AI-generated drafts require human oversight, the time saved on initial drafting is significant.

Beyond content generation, participants noted that AI can also automate aspects of grading and feedback, although such applications remain largely exploratory. Several interviewees described pilot projects in which AI systems produced preliminary assessments of student assignments, flagging common errors and suggesting potential improvements. These initiatives were intended to reduce the marking workload of academic staff while providing students with faster, more consistent feedback.

However, participants stressed the importance of maintaining human oversight to safeguard academic integrity and quality standards. As one finance manager explained:

“We tested AI-assisted grading for multiple-choice quizzes; it worked well, but we still check the outputs to make sure there’s no bias or errors”.

These examples highlight how AI can streamline academic workflows and improve turnaround times, while underscoring that automation must complement (not replace) human judgment in higher education.

Interpretation of AI-Driven Operational Efficiency Gains: The AI-driven operational efficiency gains theme highlights that universities perceive GenAI as a mechanism for increasing productivity and service quality without proportionally raising costs. The automation of administrative processes enables staff to manage larger workloads within existing staffing levels, while AI-powered analytics support faster, data-driven decisions that prevent inefficiencies and improve outcomes. Streamlined academic and support workflows also free up time for teaching, research, and strategic initiatives, enhancing the overall experience for students and staff alike.

Collectively, these efficiency gains allow universities to “remove friction” from key processes, as one participant described, enabling institutions to adapt to growth and operational complexity while maintaining financial stability and resource balance. The evidence answers RQ1 by demonstrating that generative artificial intelligence not only reduces costs but also improves the cost-to-output ratio, which is a critical component of financial sustainability.

Integration of Findings and Implications for Cost Management

The themes of AI-driven cost savings and AI-driven operational efficiency gains are closely interconnected. In many cases, initiatives designed to reduce costs also

enhance efficiency, and vice versa. For example, automating invoice processing simultaneously lowers labour expenditure and accelerates transaction handling. Similarly, real-time expenditure dashboards not only prevent overspending but also improve the speed and accuracy of managerial decisions. These synergies illustrate how AI contributes to financial sustainability through multiple, mutually reinforcing mechanisms.

Participants noted that the most significant cost pressures within universities relate to personnel and operational expenses. Salaries and benefits often account for more than half of total university expenditure, sometimes nearing sixty percent of total revenue. Across interviews, respondents consistently emphasised that GenAI can help institutions manage these pressures by enabling service growth without proportional increases in staffing levels. As one Information Technology Director explained:

“Instead of hiring more staff, we lean on automation to extend the team’s capacity”.

This approach allows universities to maintain fiscal discipline while responding to increasing demands from students, funders, and regulatory bodies.

Findings also suggest that AI initiatives are most effective when implemented alongside robust financial monitoring and policy compliance mechanisms. Participants valued AI systems that could monitor procurement, flag policy deviations, and detect potential fraud in real time. Such tools reinforce a culture of financial accountability and ensure that cost savings are not undermined by inefficiencies or non-compliance. The integration of real-time monitoring with strategic forecasting provides finance leaders with a holistic view of their institution’s financial position, empowering them to act proactively to control expenditure.

Finally, the findings reveal varying levels of AI maturity across institutions. Some universities have begun with small-scale automation pilots, while others are integrating AI into budgeting and analytics functions. Despite these differences, there is broad consensus on GenAI’s potential to support sustainable cost management. Even where adoption remains exploratory, participants agreed that early pilots are building institutional learning and readiness for more advanced implementations in the future. This willingness to experiment reflects a growing recognition that

innovation is no longer optional but essential for long-term financial sustainability in higher education.

Cost management and efficiency summary

This section has presented the findings related to RQ1, examining how GenAI contributes to cost management and operational efficiency within South African universities. Two overarching themes (AI-driven cost savings and AI-driven operational efficiency gains) emerged from the thematic analysis of nine interviews with senior university stakeholders. Within these themes, sub-themes captured areas such as the automation of routine administrative tasks, the use of analytics to identify non-essential expenditure, data-driven budgeting, enhanced decision-making, and the streamlining of academic and support workflows. Participant quotations illustrated practical examples of cost reduction and efficiency improvements, demonstrating that AI technologies are already being applied in multiple dimensions of university operations.

The findings show that generative artificial intelligence is viewed as a practical tool for financial sustainability. It reduces labour and operational costs through automation, identifies and eliminates wasteful spending, supports proactive budgeting and financial control, improves the speed and quality of decisions, and enhances the productivity of both administrative and academic processes. These findings address RQ1 by showing that AI enables universities to manage costs and enhance operational efficiency even within constrained financial environments. The structured presentation of themes and sub-themes, supported by direct participant evidence, ensures that the results are communicated clearly, coherently, and in alignment with established guidelines for a results chapter.

5.2 Findings related to RQ2: revenue generation

The second research question asked how generative artificial intelligence can help universities generate new revenue or diversify existing revenue streams. Whereas the previous section focused on cost containment and efficiency gains, this section addresses the income side of financial sustainability. University leaders expressed a clear interest in using artificial intelligence to enhance revenue, recognising that long-term financial health requires both reducing costs and increasing income. The interviews revealed a major theme related to AI for Revenue Enhancement. Within this theme, three sub-themes emerged: diversification and new income streams,

optimising core revenue (through student success and pricing strategies), and enhanced fundraising and partnerships. Each sub-theme is presented below with supporting quotations and a concise analytical commentary linking the findings to RQ2.

5.2.1 THEME 3: AI FOR REVENUE ENHANCEMENT

Participants described generative artificial intelligence as more than a cost-saving tool; they saw it as an enabler of value creation. Interviewees emphasised that AI could help universities tap into new markets, improve existing revenue channels, and strengthen engagement with external stakeholders. This theme encompasses the various ways in which AI-enabled innovation, analytics, and personalised engagement can bring additional income to universities.

Sub-theme: Diversification and New Income Streams

A recurring idea among participants was that generative artificial intelligence could enable universities to launch new programs, services, or products, creating income beyond traditional revenue sources such as government subsidies and student tuition. Several interviewees referred to this as “third stream” income, a term often used in South Africa to describe non-traditional revenue streams. The concept involves developing offerings that leverage the university’s expertise and assets in artificial intelligence to serve external markets.

One ICT director described how their institution is exploring internal development of AI-powered products that could be commercialised: “We’ve even looked at developing our own AI tools, like a local language chatbot or a virtual lab simulation, that we could offer to other institutions or sell to government”. By leveraging their in-house expertise, universities could create digital products that cater to local needs. Locally developed AI chatbots could be deployed to support government services or other educational institutions, while virtual laboratory simulations could be licensed to schools and training centres. This illustrates a strategic approach in which universities leverage their research and technical capabilities to generate additional revenue through the commercialisation of software and digital services.

Participants also discussed offering AI-based training and education programs as a way to diversify income. A CFO noted the market for short courses on AI and data science: “There’s a market for courses on AI and data science. If we create those programs using our AI capabilities, we attract new students and new fees”.

Universities can develop short learning programmes, executive education modules, or certificates in artificial intelligence and related fields (University B, 2022). These programs target working professionals or students who need up-skilling in AI. By using their AI expertise in course design and delivery, universities can expand their student base and charge fees for these new offerings. The ability to provide unique AI-driven curricula and training positions the institution as a provider of specialised skills, which is attractive in a labour market increasingly interested in digital competencies.

Another example of diversification involved the creation of AI-driven simulations and learning tools that could be licenced to other institutions or industry partners. An interviewee explained that their university is experimenting with virtual reality lab simulations: “We’re developing AI based simulations of lab experiments that can be used by schools that don’t have the resources for full lab setups”. Such tools could be sold or licenced as educational products, creating a revenue stream while also fulfilling a social mission of improving access to laboratory experiences. Participants highlighted that by developing and commercialising AI-based tools, universities could create new income streams while capitalising on their existing research and development capabilities. Beyond the education sector, several participants identified further opportunities in consulting and advisory services built on institutional expertise in AI and data analytics. Such initiatives position universities not only as centres of learning but also as knowledge partners capable of supporting external organisations in adopting and applying AI solutions

A finance executive mentioned that their institution was considering setting up an AI consulting arm:

“Our AI team could offer services to industries... for instance, advising small businesses on AI adoption or developing customised models. It’s an opportunity to earn revenue while building relationships”.

By offering AI-focused consulting services to industry, universities can monetise their research capabilities and technical expertise. These services may include developing institutional or corporate AI strategies, training professionals in applied AI, or designing customised AI solutions for specific organisational needs. Through such engagements, universities extend their societal impact while generating additional income from their intellectual capital. Consulting services provide fees and

can also lead to partnerships or research collaborations, further enhancing the university's reputation and reach.

Some interviewees suggested that AI research could lead to spin-off companies and intellectual property licensing. For example, a participant from a technology office noted:

“If our researchers develop an algorithm or tool that has commercial potential, we can patent it and licence it to industry partners”.

Through technology transfer and licensing, universities can realise financial returns on their research. Spin-off companies established to commercialise AI innovations can provide universities with long-term revenue through royalty income or equity holdings. Although these ventures require upfront investment, strategic oversight, and robust governance, participants viewed them as valuable mechanisms for translating research outputs into financial returns.

Participants also discussed collaborative ventures with industry as a complementary pathway for generating income. One ICT Director described a partnership with a technology firm to develop a local-language translation model:

“We’re working with an industry partner to build a translation model for indigenous languages; they bring funding and market access, we bring research expertise”.

Such collaborations combine academic and commercial strengths, enabling universities to co-create products or services that can be monetised through licensing, subscription fees, or shared intellectual property agreements. By combining industry funding with academic expertise, universities reduce the financial risk of product development while gaining access to commercial markets.

In summarising this sub-theme, the findings show that university leaders view generative artificial intelligence as a catalyst for diversifying income. By creating AI-based products, training programmes, consulting services, and research-driven innovations, universities can expand their revenue base beyond traditional funding sources. These initiatives are viewed as critical to achieving long-term financial sustainability, especially amid declining government subsidies and restrictions on tuition fee increases. The findings address RQ2 by illustrating how AI enables universities to diversify their income sources, enter new markets, and transform

institutional knowledge into monetisable value. Through commercialisation, partnerships, and service innovation, universities can leverage AI not only as a technological tool but as a strategic asset for financial resilience.

Sub-theme: Optimising Core Revenue (Student Success and Pricing)

While diversification targets new income sources, participants also emphasised the role of AI in optimising existing revenue streams. This sub-theme explores how AI initiatives can strengthen core income by improving student success, enhancing enrolment management, and enabling more responsive pricing strategies. Through predictive analytics, personalisation, and dynamic pricing models, AI supports higher retention rates and more efficient revenue capture. Interviewees identified several mechanisms through which these applications contribute to revenue optimisation and, ultimately, to institutional financial sustainability.

A significant portion of core revenue in South African universities comes from government subsidies linked to student completion rates, and from tuition fees. Improving student performance therefore has a direct financial impact. Many participants highlighted the potential of early warning systems that identify students at risk of academic failure or drop-out. One university executive described an intervention: “Using AI to flag at-risk students academically. By intervening earlier, we can improve their success rates... that directly affects our subsidy income because more students graduate”. By analysing course performance, attendance patterns, and other data points, AI tools can flag students who may need support. Early interventions improve retention and graduation rates, which in turn affect both subsidy funding and tuition revenue (because students who remain enrolled continue paying fees). Participants noted that such systems enable universities to focus resources on those who need help, thereby improving throughput and stabilising income.

Participants also discussed how predictive analytics can improve student recruitment. One CFO explained: “Using AI to profile the students who are most likely to succeed and who align with our programmes. By targeting the right applicants, we can increase our chances of good performance grants and reduce bad debt”. AI models can identify potential students who have a high probability of completing their studies, which helps reduce dropout rates and improve subsidy outcomes. Additionally, AI-driven marketing analytics enable universities to identify and target prospective students more effectively. By analysing application trends, demographic

data, and online engagement patterns, institutions can focus recruitment efforts on high-demand programmes and regions with the greatest enrolment potential. This targeted approach not only increases student intake but also improves utilisation of teaching capacity and facilities. As a result, universities can maximise fee-based income while maintaining alignment between market demand and programme delivery. The more accurate the recruitment strategy, the more likely the institution is to attract students who will complete their studies and pay their fees.

Another aspect of revenue optimisation concerns pricing strategies for self-funded programmes such as executive education, online courses, and short learning programmes. Although tuition fees for degree programmes are largely regulated, universities retain greater flexibility in pricing non-degree and auxiliary offerings such as short courses and executive education. Participants observed that AI can assist in analysing market dynamics and identifying optimal price points for these programmes. One finance manager explained:

“We could use AI to analyse demand for our courses and set prices for short courses dynamically to maximise our margins”.

This reflects the potential of AI-driven dynamic pricing, where fees are adjusted in response to real-time data on demand, competitor pricing, and cost structures. Such responsiveness enables universities to improve profitability and ensure that programme pricing remains both competitive and financially sustainable. For instance, if a course fills quickly, the price might be increased; if demand is low, a discount could attract more participants. AI can also assess price elasticity by analysing how variations in course fees influence enrolment patterns. Through adaptive pricing algorithms, universities can model different fee scenarios and predict their effects on student demand. This capability allows decision-makers to identify the price points that maximise revenue while maintaining accessibility. In doing so, institutions can balance profitability with equity, ensuring that pricing strategies remain financially sustainable without excluding cost-sensitive students.

Fee collection and debt management also emerged as central aspects of core revenue optimisation. Participants acknowledged that unpaid student fees continue to erode institutional income and strain liquidity. AI-based analytics can profile students using payment histories, demographic variables, and socio-economic

indicators, enabling finance teams to design targeted collection strategies. One CFO explained:

“We’re looking at AI to improve debt collection; like identifying who is likely to pay if given a reminder versus who needs a different approach”.

By segmenting students according to their likelihood of payment, universities can apply differentiated interventions (such as personalised reminders, flexible repayment options, or early engagement) to improve recovery rates. These predictive insights help institutions manage arrears more efficiently and safeguard a critical source of self-generated revenue. Even a small increase in collections can help with revenue. By tailoring communication and intervention strategies, universities can increase recovery rates. For example, some students may respond to early reminders, while others might need instalment plans or counselling. AI can segment the student population according to behavioural and financial patterns, recommending tailored interventions that improve fee recovery and strengthen institutional cash flow. By linking predictive insights to targeted follow-up actions, universities can move from reactive debt collection to proactive revenue management, ensuring greater financial stability.

Participants also noted that AI can help reduce bad debt by predicting which students are likely to default on payments, allowing institutions to manage financial risk proactively. For example, early identification of students experiencing financial distress enables universities to offer tailored interventions such as bursaries, flexible repayment arrangements, or counselling support before arrears accumulate. These measures lower the probability of fee write-offs and contribute to more stable revenue streams. One finance executive explained:

“System could flag students who might struggle to pay... we can then put them on a payment plan rather than letting debt build up”.

Such proactive engagement not only protects institutional income but also aligns with the sector’s commitment to student equity and financial inclusion.

Beyond pricing and student success, participants observed that AI can also inform strategic resource allocation decisions that indirectly influence revenue. By analysing utilisation patterns of facilities, courses, and staff workloads, AI systems can identify areas of over- or under-investment, enabling institutions to reallocate resources toward higher-yield programmes or more efficient service delivery. For example,

predictive models of course demand can help universities decide which programs to expand or phase out. If data indicate that demand for a certain programme is declining, the university might reduce intake to avoid running underutilised classes that drain resources. Conversely, data showing high demand can justify investment in additional teaching capacity, which can generate more revenue. One ICT director explained:

“We can use AI to forecast course demand... helping us decide where to invest in lecturers and facilities, so we don’t waste resources on programmes that aren’t viable”.

By aligning teaching resources with student demand, universities can optimise their return on investment and improve capacity utilisation. This ensures that funding, staff time, and infrastructure are concentrated in high-demand programmes that generate sustainable income, while low-yield activities are restructured or phased out. In doing so, AI not only enhances operational efficiency but also strengthens the revenue base by linking resource allocation directly to market demand.

In summary, this sub-theme shows that AI plays a significant role in maximising core revenue. By improving student recruitment and success, enabling dynamic pricing strategies, assisting fee collection, and informing resource allocation, artificial intelligence helps universities secure and grow their existing income streams. The evidence answers RQ2 by illustrating how AI initiatives improve the financial performance of existing operations, complementing the diversification of revenue sources.

Sub-theme: Enhanced Fundraising and Partnerships

The third sub-theme examines how AI supports fundraising and the cultivation of external partnerships. Participants emphasised that GenAI can assist in identifying and engaging potential donors, matching researchers with relevant grant opportunities, and strengthening collaborations with industry. Collectively, these functions enhance institutional revenue through increased philanthropic contributions, research income, and partnership-driven projects.

Fundraising emerged as a recurring theme across interviews. Many universities maintain extensive alumni databases yet identifying high-potential donors and sustaining meaningful engagement remain persistent challenges. AI tools were viewed as valuable in addressing this issue by analysing historical donation records,

engagement trends, and demographic profiles to predict giving likelihood. By segmenting donor groups and personalising communication, universities can run more targeted and cost-effective fundraising campaigns, thereby increasing conversion rates and long-term donor loyalty. Instead of sending generic requests to a broad group, fundraising teams can focus on those with higher giving potential, resulting in higher response rates and larger gifts.

Participants also highlighted that AI has the potential to generate personalised engagement strategies to strengthen donor relations. By analysing individual engagement patterns and aligning outreach to personal motivations, universities can cultivate deeper, more meaningful connections with donors. This personalised approach transforms fundraising from a generic, one-size-fits-all exercise into a targeted, data-driven strategy that resonates with donor values and increases the likelihood of sustained giving.

In addition to alumni and donors, AI can support the identification of corporate sponsorship and partnership opportunities. One finance executive stated: “AI could improve how we engage donors... we know who to talk to and what projects might interest them, which ultimately boosts fundraising”. By analysing networks and corporate interests, AI can identify companies that may benefit from associating with university programmes or research projects. Understanding which companies prioritise specific research domains or social causes enables universities to approach potential sponsors with proposals that closely align to their strategic interests. This targeted matching increases the likelihood of securing corporate funding or sponsorships.

Beyond donor engagement, participants noted that AI could also add significant value in linking researchers to relevant grant opportunities and collaborative partners. By scanning large databases of funding calls, research publications, and institutional profiles, AI systems would identify where a university’s expertise aligns with available grants or industry needs. This capability not only reduces the administrative burden of grant searches but also broadens access to funding opportunities that might otherwise be overlooked.

By scanning databases of research funding programmes and industry needs, AI can recommend grant calls that align with researchers’ expertise. Similarly, participants noted that AI can help identify companies actively seeking research collaborations,

thereby facilitating partnerships that provide funding, equipment, or technical expertise to universities. These collaborations extend beyond immediate financial gains by strengthening institutional reputation, research capacity, and external networks. As several interviewees observed, partnerships initiated through AI-driven matching tools often evolve into long-term relationships that yield ongoing grants, joint publications, and innovation opportunities. In this way, AI contributes not only to short-term revenue but also to the sustained growth and visibility of universities within national and international research ecosystems.

AI can also help manage and strengthen existing partnerships. For example, participants explained that AI systems can monitor the performance of collaboration agreements, track deliverables, and detect potential risks before they jeopardise relationships. A finance manager shared:

“We can use AI to track our partnership agreements and make sure we deliver on time and within budget. This ensures partners stay satisfied and consider future collaborations”.

Such proactive oversight safeguards revenue streams by ensuring compliance with contractual obligations and maintaining partner confidence. Effective partnership management, supported by AI, therefore not only protects existing income but also strengthens the likelihood of contract renewals, expanded agreements, and new funding opportunities.

Participants acknowledged that adopting AI for fundraising and partnerships requires investment in data management and system integration. Accurate data are essential for predictive models to work. The interviews indicated that universities are aware of this requirement and are actively working to strengthen their data quality, governance, and analytics capabilities. Participants described efforts to consolidate fragmented information systems, clean existing datasets, and develop internal dashboards that support more reliable decision-making. These improvements were viewed as foundational for the effective deployment of AI solutions, since high-quality data directly influences the accuracy and usefulness of analytical outputs. Some interviewees indicated that they are still in the early stages of implementing AI in fundraising, while others have established pilot projects. Nonetheless, participants agreed that AI-enhanced fundraising and partnerships offer significant potential for generating new revenue.

The evidence in this sub-theme demonstrates that AI can transform how universities identify, engage, and retain donors while also strengthening research and industry collaborations. By analysing donor data, matching researchers with relevant funding opportunities, and supporting more transparent management of partnership agreements, AI contributes to the growth and stability of external income streams. Within the South African context (where donations and collaborations form a critical part of university funding) AI was viewed as a practical tool to expand these financial channels. Overall, the findings address RQ2 by showing that AI not only opens new avenues for revenue generation but also deepens institutional relationships that yield lasting financial and reputational benefits

Integration of Findings and Implications for Revenue Generation

The findings across the three sub-themes demonstrate the wide-ranging potential of GenAI to strengthen university revenue streams. Diversification initiatives enable institutions to generate new income through innovative products, services, and training programmes. Optimisation efforts enhance existing revenues by improving student success, applying dynamic pricing, and strengthening fee collection systems. AI-supported fundraising and partnerships further expand income by identifying and engaging donors more effectively, aligning proposals with relevant funding calls, and deepening corporate and research collaborations. Collectively, these strategies represent a holistic approach to revenue growth that complements the cost-saving and efficiency gains discussed earlier.

A central insight from the interviews is that sustainable revenue enhancement depends on balancing innovation with optimisation. AI allows universities to enter new markets and develop novel offerings, while simultaneously refining internal processes to maximise existing income. However, realising these benefits requires investment in digital infrastructure, sound data management, and effective integration of AI tools into institutional systems. Participants consistently emphasised that while AI provides the analytical power and scalability, human expertise, ethical judgement, and strategic oversight remain indispensable for converting insights into tangible financial outcomes.

Finally, the findings underline the need to align revenue initiatives with institutional purpose. Interviewees expressed the importance of ensuring that commercial or income-generating activities do not compromise academic integrity or social

responsibility. For instance, the development of AI-based products should remain consistent with the university's educational mission, and pricing models must consider affordability and inclusivity. When AI-driven initiatives are embedded within a clear strategic and ethical framework, universities can pursue financial sustainability in a way that reinforces, rather than dilutes, their core values.

Revenue generation summary

This section has presented the findings related to RQ2, which examined how GenAI can support universities in generating new revenue and strengthening existing income streams. The overarching theme of AI for Revenue Enhancement comprised three interrelated sub-themes: (1) diversification and the creation of new income opportunities, (2) optimisation of core revenue sources through improved retention, pricing, and collection, and (3) enhanced fundraising and partnerships that leverage AI for donor engagement and collaboration management. Together, these sub-themes demonstrate that AI enables universities to adopt a more proactive and data-driven approach to revenue generation, positioning them to achieve greater financial resilience in an increasingly resource-constrained environment. Through examples and quotations from senior university stakeholders, the findings showed how universities are developing AI-based products, training programmes, and services; using predictive analytics to improve student success and pricing strategies; and leveraging AI to identify and engage donors and partners. These initiatives demonstrate that AI plays a multifaceted role in revenue generation.

The evidence suggests that GenAI equips universities with the capability to extend their reach beyond conventional funding sources while simultaneously reinforcing existing revenue channels. By combining data-driven insight with automation and predictive analytics, universities can identify new market opportunities, enhance financial performance, and diversify income in ways that were previously unattainable. These findings underscore the transformative role of AI not only as a technological innovation but also as a strategic enabler of long-term financial sustainability. By diversifying income sources, optimising core revenue processes, and enhancing engagement with donors and partners, universities can improve their financial resilience. These findings answer RQ2 by showing that AI is not only a cost management tool but also a catalyst for revenue creation. When combined with the cost saving and efficiency gains described earlier, AI offers a two-pronged approach to achieving financial sustainability in the South African higher education sector.

5.3 Cross-cutting themes: AI adoption factors

The research questions focused on how generative artificial intelligence might reduce costs and enhance revenue in South African universities. Yet, the interviews made clear that the potential financial benefits of AI cannot be realised in isolation from broader institutional conditions. Across all nine interviews, participants described factors that either impede or enable AI adoption, and warned of risks that require careful management. These cross-cutting themes apply to both RQ1 and RQ2 because they frame the context in which AI initiatives operate. They do not directly reduce costs or generate income, but they determine whether AI projects will be possible, sustainable and beneficial. This section presents the cross-cutting themes organised into three categories: barriers to AI adoption, risks of AI implementation and use, and enablers and prerequisites for success. Within each category, sub-themes capture specific issues raised by participants. By understanding these factors, we gain insight into the organisational landscape that must be navigated to achieve AI-driven financial sustainability.

5.3.1 THEME 4: BARRIERS TO AI ADOPTION

Despite enthusiasm for AI's potential, participants identified a number of obstacles that slow or prevent implementation. These barriers are pre-adoption hurdles: they relate to the readiness of people, culture, technology, finances and strategy. If not addressed, they make it difficult to deploy AI solutions that deliver cost savings or generate revenue. The sub-themes below summarise the principal barriers identified in the interviews.

Sub-theme: Limited Skills and AI Literacy

A recurring barrier was the shortage of digital skills and AI literacy among staff and even leaders. Participants acknowledged that many employees lack the technical knowledge needed to engage with AI tools or interpret AI outputs. One CFO candidly rated her institution's readiness as "maybe four out of ten" in terms of digital and AI capability. This low baseline means that many available AI tools remain underutilised or are misunderstood by staff. Several participants noted that employees hesitate to experiment with AI because of limited familiarity or fear of making mistakes. The lack of structured training programmes compounds this challenge, as most staff must rely on self-learning or informal peer support. Consequently, adoption tends to be slow, with few individuals possessing the skills or confidence to pilot and scale AI

initiatives. The skills gap also extends to senior decision-makers; some leaders lack a clear understanding of AI's practical potential and constraints, which hampers their ability to make informed investment or policy decisions. Without a workforce that both understands and trusts AI, even basic automation efforts struggle to gain traction.

The interviews further revealed that AI literacy is unevenly distributed across departments. Technical faculties such as computer science or information technology often house small clusters of expertise, while administrative and academic units remain largely untrained. This disparity results in isolated innovation rather than coordinated, institution-wide transformation. Participants agreed that closing this skills gap is critical to achieving meaningful and sustainable AI integration across the university ecosystem. A finance director noted that only about sixteen percent of people actively lead change in any organisation; without targeted efforts to raise skills across the board, AI adoption may remain confined to a few early adopters. The skill gap is thus a fundamental barrier that must be addressed through deliberate training, recruitment and knowledge sharing.

Sub-theme: Resistance to Change and Cultural Barriers

Participants consistently identified organisational culture as one of the most significant barriers to AI adoption. Universities were often described as hierarchical, bureaucratic, and risk-averse; structures that mirror government departments more than agile, innovative organisations. Such cultures tend to favour established routines and discourage experimentation with new technologies. Several interviewees observed that some employees fear that AI might threaten their roles or undermine their professional expertise, leading to overt resistance or subtle non-cooperation. One participant noted that certain staff members “still prefer paper-based processes because they don't trust digital systems”. These perceptions create a climate of scepticism in which AI is viewed less as a supportive tool and more as a potential disruptor. Effective change management was therefore seen as essential to countering these fears and building trust in AI-driven processes.

Cultural barriers also emerged in the form of slow decision-making and limited innovation appetite. Even when AI pilots demonstrated value, participants described how bureaucratic procedures frequently delayed approvals or stalled implementation. Leaders were said to hesitate in endorsing projects due to concerns about reputational risk or possible failure. This cautious stance reinforces a culture of compliance rather than experimentation, making it difficult for institutions to scale

successful initiatives. Resistance is not confined to staff alone; students, too, were reported to express unease about AI tools; particularly regarding fairness, privacy, and academic integrity. Participants agreed that transparent communication and inclusive engagement are necessary to address these anxieties and cultivate a culture of trust and learning.

In summary, deeply embedded cultural conservatism and fear of change generate inertia that slows AI adoption and can derail even well-designed initiatives. Overcoming these barriers requires sustained leadership commitment, clear messaging, and a deliberate shift towards an institutional culture that values innovation, collaboration, and responsible risk-taking.

Sub-theme: Technological Infrastructure Limitations

Modern AI systems depend on reliable infrastructure and high-quality data, yet many participants stressed that their institutions continue to rely on outdated IT systems, fragmented data environments, and manual processes. This technological debt severely constrains the deployment of AI tools. One ICT director compared the challenge to “buying an HDTV with no decoder”; the advanced technology cannot perform without an appropriate foundation. In several universities, data were described as siloed, inconsistent, and incomplete. Poor data quality, participants explained, undermines the reliability of machine-learning outputs and weakens confidence in analytical insights. The familiar phrase “garbage in, garbage out” was repeatedly invoked to illustrate how weak data governance translates into flawed AI performance.

The absence of modern infrastructure also limits performance and scalability. Participants noted that cloud computing, high-performance servers, and integrated platforms are prerequisites for running advanced AI models effectively. Without these enablers, pilot projects are often executed on underpowered local machines or depend on external vendors, introducing additional cost and complexity. Some interviewees mentioned that specific AI applications could only operate through third-party providers because institutional servers lacked the required capacity. This dependence slows implementation, especially when procurement procedures are lengthy or budgets are constrained. Collectively, these limitations underscore that universities cannot simply purchase AI systems “off the shelf”. Sustainable adoption requires upgrading network capacity, storage, and computing resources, as well as

establishing robust data management and governance frameworks to ensure trustworthy and scalable AI use.

Sub-theme: Financial Constraints

Ironically, many universities pursue AI to achieve financial sustainability yet struggle to fund the very investments required to implement it. Several participants described their institutions' funding models as increasingly unsustainable, citing declining government subsidies and limited flexibility to raise tuition fees. These pressures leave little fiscal space to support new technology initiatives. As one CFO remarked, it is a "catch-twenty-two" situation; universities need AI to reduce costs and increase revenue, but they lack the upfront capital to purchase software, upgrade infrastructure, or train staff. In South Africa, where many universities already operate with structural deficits, major technology investments are often difficult to justify.

Participants highlighted that AI projects typically demand multi-year commitments. Costs are incurred early, while benefits may take years to materialise. In this context, finance committees are hesitant to approve large-scale expenditure without clear or immediate returns. Several leaders recalled previous digital transformation efforts that failed to deliver expected value, creating lingering caution toward new initiatives. Even when external funding or donor support is available, it is often earmarked for research activities rather than operational improvements. Consequently, promising AI initiatives are frequently postponed, downsized, or discontinued due to financial constraints.

These findings underscore that sustainable AI adoption requires a deliberate financing strategy. Participants suggested approaches such as reallocating internal budgets, forming partnerships with technology providers, or pursuing targeted grants to offset upfront costs. Ultimately, a credible business case (clearly articulating both short-term efficiencies and long-term value creation) is essential to secure investment and build institutional confidence in AI implementation.

Sub-theme: Lack of Strategy or Policy

A final barrier identified by participants was the absence of a clear institutional AI strategy and governance framework. In the absence of a coordinated plan, AI efforts tend to emerge in an ad hoc and fragmented manner. Several interviewees remarked that "everyone is doing their own thing", with departments launching isolated pilots without alignment or oversight. This uncoordinated approach often results in

duplication, inconsistent standards, and wasted resources. For instance, different units may independently procure overlapping tools or engage separate vendors, leading to redundancy and inflated costs. Participants also noted that without overarching policies, there is limited guidance on issues such as data privacy, ethical use, or system integration. This uncertainty discourages adoption, as staff may be hesitant to use AI tools for fear of breaching regulations such as the POPIA.

Some interviewees further explained that their institutions lacked a formal AI roadmap or designated governance structure to oversee digital innovation. In such environments, AI initiatives compete for attention alongside other strategic priorities, without consistent evaluation criteria or clear leadership ownership. This results in organisational ambiguity: staff await direction, while senior leaders delay decisions to avoid missteps. As one CIO cautioned, without a unified strategy and governance model, AI adoption risks becoming “a collection of isolated projects with little cumulative impact”. Participants agreed that establishing a coherent institutional framework (defining roles, responsibilities, ethical standards, and evaluation mechanisms) is essential to achieve coordinated and sustainable AI integration. Creating policies and strategic plans is therefore essential to provide direction, coordinate efforts, and ensure that AI aligns with institutional goals. A governance structure can also facilitate risk management and oversight, which is necessary to address the next category of cross-cutting themes.

Interpretation of Barriers: These barriers illustrate that adopting AI is not merely a technical task but an organisational transformation. Skills must be built, culture must evolve, infrastructure must be upgraded, funding must be secured, and strategy must be established. Without addressing these preconditions, the cost-saving and revenue-generating benefits of AI will remain elusive. In the context of the research questions, the barriers help explain why universities have yet to fully realise AI's potential for financial sustainability. They provide the background against which the success or failure of AI initiatives can be understood.

5.3.2 THEME 5: RISKS OF AI IMPLEMENTATION AND USE

Beyond barriers that impede adoption, participants were keenly aware of risks associated with AI. These risks arise once AI systems are in use and relate to academic integrity, privacy, ethics, reliability and return on investment. If these risks are not managed, the financial gains from AI could be neutralised by negative

outcomes. The sub-themes below summarise the main risk categories identified in the interviews.

Sub-theme: Academic Integrity and Misuse

A prominent risk is that GenAI could undermine academic integrity. Interviewees expressed concern that students or staff might misuse AI tools to plagiarise, cheat or bypass learning. For example, a CISO described the sudden availability of large language models as a “wake-up call for our assessment methods”. Traditional written assignments and take-home tests may be easily completed by an AI, raising questions about authenticity. Participants emphasised that universities must adapt assessment practices, perhaps by increasing oral exams, project-based work or supervised tasks, to ensure genuine learning. Some universities have begun experimenting with AI-generated content detection tools; however, participants cautioned that the rapid pace of AI development makes it difficult to depend on detection alone. Systems designed to identify AI-produced text often lag behind newer models, reducing their reliability. In addition, several interviewees expressed concern that staff might themselves misuse AI to expedite marking, generate reports, or simplify administrative work, potentially compromising academic and operational quality. Addressing these risks, participants argued, requires more than technical safeguards. Institutions must establish clear policies defining ethical AI use, educate students and employees on responsible practices, and maintain continuous oversight to monitor and manage potential misuse.

Sub-theme: Data Privacy and Security Risks

AI tools typically rely on user-provided data to operate effectively. Several participants expressed concern that this requirement could inadvertently expose sensitive or confidential information. They noted that staff and students may, often unknowingly, input personal data, student records, or institutional documents into external AI platforms, creating potential breaches of privacy and data protection regulations. The risk is heightened when cloud-based services store or process information outside the university’s control. Participants emphasised that without clear guidelines and technical safeguards, such practices could compromise compliance with data protection laws and undermine institutional trust. Strengthening internal data governance, raising awareness about secure AI use, and implementing approved platforms were identified as key measures to mitigate these risks. South African universities must comply with data protection regulations such as POPIA.

One ICT director shared that they halted the use of an AI note-taking app campus-wide until a policy was in place, to avoid accidental data breaches. Universities may not know where data are stored or how they will be used by third-party AI providers. Participants also warned that AI systems themselves could become targets for cyberattacks if not adequately protected. Several likened AI adoption to earlier cybersecurity efforts, noting that every new tool introduces potential vulnerabilities that must be carefully managed. They emphasised that AI applications should be tested in controlled environments and subjected to thorough security assessments before deployment. Without clear governance policies and technical safeguards, universities risk exposing sensitive student and staff data to unauthorised access or misuse. The consequences of a breach (ranging from regulatory penalties and reputational harm to the financial cost of remediation) could easily outweigh the intended benefits of adopting AI. These insights highlight the importance of embedding cybersecurity considerations into all stages of AI implementation, from procurement to ongoing monitoring.

Sub-theme: Bias and Ethical Concerns

Participants also identified bias in AI models as a major ethical and operational risk. They cautioned that when AI systems are trained on historical data containing embedded biases, the resulting models may accidentally reproduce or even amplify existing inequities. For example, predictive analytics tools that classify students as “at risk” could disproportionately target certain groups if the underlying data reflect past disparities. A finance executive warned that such systems might profile individuals into “risk personas”, potentially leading to unfair treatment or exclusion.

Concerns about transparency and accountability were also raised. Staff and students often have limited understanding of how AI-generated decisions are made, which can erode confidence in the technology and the institution deploying it. Participants emphasised the importance of implementing bias testing, fairness audits, and mechanisms for explaining AI decision processes in accessible language. They underscored that universities have a moral and legal duty to ensure fairness, inclusivity, and accountability in all technology-driven processes. Failure to address bias, participants warned, could harm individuals, damage institutional reputation, and invite increased scrutiny from regulators or the broader public.

Sub-theme: Reliability and Oversight

AI systems can produce errors or “hallucinations”, plausible sounding but incorrect information. Participants acknowledged that AI may sometimes be “confidently wrong”. Blindly trusting AI outputs could lead to incorrect decisions, particularly in high-stakes areas such as admissions, budgeting or academic advising. One academic director cautioned that human oversight is necessary: “You can’t blindly trust it”. Over-reliance on AI without human review could erode human expertise; staff might lose the ability to perform tasks manually or critically evaluate AI suggestions. Participants emphasised a “human in the loop” approach, where AI assists rather than replaces human judgement. For instance, while AI can efficiently generate reports or summaries, a qualified person must still review, validate, and authorise the final output. Clear accountability frameworks are necessary to ensure that ultimate responsibility rests with individuals, not algorithms. Without such oversight, AI tools could unintentionally introduce errors or inaccuracies that carry significant financial, operational, or academic consequences.

Sub-theme: Implementation and Return on Investment Risks

A final risk is that AI projects may fail to deliver value or may waste resources if poorly planned. Participants warned against succumbing to hype. One CFO noted that it is easy to invest in AI without a solid business case: “It’s easy to get swept up by the hype and invest in AI without a solid business case”. Projects may be launched without clear objectives, user buy-in or understanding of costs. Another concern raised by participants was the growing risk of tool spread, in which separate departments procure overlapping AI applications without central coordination. This fragmented approach leads to duplication of functionality, inconsistent data management, and unnecessary expenditure. Participants noted that when resources are dispersed across multiple systems, institutions lose the opportunity to benefit from shared infrastructure, integrated analytics, and economies of scale. Coordinated procurement and governance mechanisms were therefore seen as essential to ensure that AI investments deliver collective rather than isolated value. Participants recounted past failures with large IT projects that lacked proper scoping or change management; those experiences make them cautious. A failed AI project could result in sunk costs and disillusionment. Moreover, participants cautioned that if AI initiatives fail to deliver measurable outcomes, stakeholders are likely to question the justification for continued investment. To reduce this risk, they emphasised the importance of rigorous planning, phased implementation, and systematic cost–

benefit analysis before scaling projects. Pilot testing was viewed as a practical way to assess value and identify unintended challenges early. Effective governance structures are therefore essential to ensure that AI projects remain aligned with institutional strategy and that their performance is monitored against clearly defined metrics. By linking accountability to measurable results, universities can build confidence in AI initiatives and demonstrate tangible returns on investment.

Interpretation of Risks: The detailed discussion of risks illustrates that university leaders approach AI adoption with caution and pragmatism. They recognise its potential to improve efficiency, reduce costs, and generate new revenue streams, yet remain acutely aware that missteps could lead to significant harm. Ethical breaches, data leaks, biased algorithms, or failed implementations were all identified as threats that could erode trust and impose financial or reputational costs. Importantly, these risks intersect with both research questions: a data breach could nullify cost savings, while algorithmic bias could undermine revenue by discouraging students, donors, or partners. Effective risk management is therefore not peripheral but central to any AI strategy. Universities require clear policies, ethical governance frameworks, and active oversight to ensure that anticipated benefits outweigh potential harms. By acknowledging these limitations, institutional leaders set realistic expectations and reinforce the principle that financial sustainability must be pursued responsibly and transparently.

5.3.3 THEME 6: ENABLERS AND PREREQUISITES FOR SUCCESS

While the preceding section outlined barriers and risks, participants also identified several factors that facilitate AI adoption and help mitigate these challenges. These enablers represent the organisational conditions and strategic actions that make successful implementation possible, allowing universities to realise cost savings, enhance efficiency, and generate new revenue. In essence, they serve as the positive counterparts to the previously discussed barriers. The following sub-themes summarise the key enablers that emerged from the interviews and explain how these factors support effective and sustainable AI integration within South African universities.

Sub-theme: Leadership Support and Vision

Strong and visible leadership commitment emerged as the foremost enabler of successful AI adoption. Participants consistently emphasised that GenAI initiatives

gain real traction when senior executives actively champion digital innovation. When Vice-Chancellors, CFOs, or CIOs publicly endorse AI projects and allocate resources, it sends a powerful signal that such initiatives are an institutional priority. One interviewee observed that clear leadership vision “cuts through bureaucracy” and empowers innovators to act with confidence. By establishing digital transformation portfolios or appointing dedicated AI leads, universities demonstrate that these initiatives are integral to their strategic direction rather than peripheral experiments. Leadership support also plays a crucial role in mobilising resources, legitimising experimentation, and cultivating a culture that embraces change and continuous improvement. Participants commented that when leaders visibly back AI, staff are more willing to participate and adopt new tools. Leadership endorsement also provides cover for early adopters who may otherwise face scepticism from peers.

Sub-theme: Strategic Planning and Governance

A clearly articulated strategy and governance framework was identified as another critical enabler of effective AI adoption. Participants noted that institutions with formal AI roadmaps or policies are better positioned to align projects with their strategic objectives and prevent fragmentation. Strategic planning provides direction by identifying priority areas, defining use cases, and establishing transparent criteria for evaluating initiatives. Several universities had created cross-functional steering committees or governance boards to coordinate AI activities across finance, technology, academic, and administrative domains. These structures promote coherence and ensure that decisions consider both operational and ethical implications. Governance frameworks also set standards for data privacy, fairness, and security, reducing the risk of duplication or non-compliance. By providing clear guidance channels and approval mechanisms, governance fosters confidence and accountability. Ultimately, institutions that invest in structured planning and oversight create an enabling environment for responsible and sustainable AI integration.

Sub-theme: Infrastructure and Data Readiness

Investment in modern infrastructure and sound data management emerged as a fundamental enabler of effective AI adoption. Participants consistently highlighted that without reliable digital systems and high-quality data, even the most advanced AI tools are unlikely to deliver meaningful results. Upgrading legacy platforms, migrating to cloud environments, and implementing integrated data warehouses

were identified as essential first steps. Universities that have strengthened their network capacity, centralised data storage, and adopted cloud-based solutions were viewed as better positioned to scale AI initiatives. Data readiness also involves establishing clear governance mechanisms for data quality, cleaning existing datasets, and standardising data collection processes. In several cases, participants mentioned partnerships with external organisations or the use of grant funding to enhance infrastructure and data pipelines. While these investments may not generate immediate financial returns, they create the technical foundation required for sustainable and accurate AI deployment. Without this groundwork, AI initiatives risk remaining fragmented or producing unreliable outcomes.

Sub-theme: Skilling and Training Initiatives

Bridging the skills gap was identified as another critical enabler of successful AI adoption. Participants described a range of initiatives designed to enhance AI literacy across the institution, including specialised training for IT professionals, workshops for finance and administrative staff, and awareness sessions for faculty and students. Some universities have introduced short courses in local languages to make AI concepts accessible to non-technical personnel. One executive stressed the importance of inclusivity, noting that “training should reach everyone, from administrators to library staff, so that no one is left behind”. Expanding AI competence across all staff levels helps reduce anxiety and resistance while empowering employees to identify and implement AI-driven solutions. Skill development also strengthens internal capacity, thereby reducing dependence on external consultants. As confidence grows, staff begin to experiment with automation, analytics, and process improvement within their own units. In this way, training functions not only as an enabler of adoption but also as a catalyst for continuous innovation and organisational learning.

Sub-theme: Phased Implementation and Quick Wins

Adopting a phased implementation approach was widely recognised as a practical and risk-mitigating strategy for successful AI integration. Rather than launching large-scale, resource-intensive projects, participants recommended beginning with small, well-defined pilots that can deliver visible and measurable outcomes. This incremental approach allows institutions to experiment, learn, and build confidence before committing substantial investment. For instance, deploying a chatbot in one administrative department can demonstrate value and operational benefits, thereby

generating organisational buy-in for broader rollout. Early pilots help overcome scepticism by producing quick wins, freeing up staff time, and providing tangible evidence of AI's potential. They also serve as learning laboratories, enabling refinement of tools, adjustment of governance processes, and better understanding of institutional readiness. By progressing in stages, universities can manage expectations, contain financial exposure, and align adoption with existing capacity and infrastructure. The phased model thus promotes sustainable growth in AI capability while reducing the likelihood of costly missteps.

Sub-theme: Collaboration and Partnerships

Collaboration (both internal and external) emerged as a critical enabler of successful AI adoption. Internally, cross-functional cooperation ensures that projects draw on diverse areas of expertise. When finance, IT, and academic departments collaborate, they are able to design solutions that are technically robust, financially feasible, and educationally relevant. Establishing multi-disciplinary working groups or project teams also promotes co-creation by involving end users in the design and implementation process, which in turn enhances buy-in and practical relevance. Externally, partnerships with technology companies, industry associations, peer universities, and government agencies were viewed as essential for accessing resources, technical expertise, and emerging knowledge. Some institutions also involve students and researchers as active partners in AI initiatives; for instance, computer science students developing campus applications that simultaneously build their skills and contribute to institutional innovation. Participants further highlighted the value of engaging in professional networks, conferences, and forums to exchange lessons and benchmark progress. Such collaborations not only expand institutional capacity but also open pathways to joint projects, funding opportunities, and knowledge sharing that accelerate AI maturity across the higher education sector.

Interpretation of Enablers: Collectively, these enablers establish the organisational conditions necessary for successful AI adoption. Leadership vision, strategic planning, and governance frameworks provide overall direction and accountability. Modern infrastructure and high-quality data create the technical foundation on which AI solutions can operate effectively. Training and capacity development cultivate the human capital required to design, manage, and sustain innovation. Phased implementation enables experimentation and confidence-building through

manageable pilot projects, while collaboration (both internal and external) amplifies institutional capability through shared expertise and resources. When these dimensions align, the cost-saving and revenue-enhancing applications outlined in earlier sections are far more likely to succeed. Enablers are therefore not peripheral but central to realising financial sustainability through AI. Without them, even promising technologies may underperform or fail to scale. In relation to the research questions, these findings suggest that achieving sustainable financial outcomes through AI depends as much on organisational readiness and governance as on the technology itself.

Cross-cutting themes summary

The cross-cutting themes of barriers, risks, and enablers provide a holistic perspective on AI adoption in South African universities. Together, they illuminate why some initiatives succeed while others stall, and they contextualise the findings on cost reduction and revenue generation. The barriers reveal systemic challenges: skills shortages, cultural resistance, outdated infrastructure, funding limitations, and the absence of cohesive strategies. The risks highlight potential pitfalls such as academic misuse, privacy breaches, algorithmic bias, unreliable outputs, and poor returns on investment. In contrast, the enablers outline a pathway for overcoming these constraints and mitigating associated risks.

Collectively, these insights confirm that leveraging AI for financial sustainability is not a purely technical exercise but a complex organisational transformation. Sustainable implementation demands simultaneous investment in human capability, cultural change, infrastructure modernisation, strategic planning, ethical governance, and cross-sector collaboration. The financial gains reported in the cost-saving and revenue-enhancing themes can only be realised when these foundational conditions are in place. Conversely, neglecting them could nullify any benefit; for example, an AI tool that reduces expenses but exposes sensitive data could generate reputational and financial damage far greater than its savings. Similarly, launching new AI-based initiatives without addressing resistance or competence gaps may lead to underutilisation or outright failure.

The findings further suggest that South African universities are at different stages of digital readiness. Some institutions have begun developing policies, upgrading systems, and piloting AI projects, while others remain focused on basic digital

transformation. The cross-cutting themes therefore serve as a diagnostic framework to help institutions assess their current maturity and prioritise interventions. For example, those lacking skilled personnel may prioritise training and literacy programmes, while those constrained by legacy systems may focus on infrastructure renewal and funding models. Across all contexts, developing ethical and data-protection policies is essential before scaling AI solutions. Institutional leaders should continuously evaluate their progress against each barrier and enabler, using these insights to guide policy, investment, and capability building.

Finally, these cross-cutting dynamics highlight that the path toward AI-enabled financial sustainability is iterative rather than linear. Enablers must evolve alongside technology, barriers may shift as new systems emerge, and novel risks will arise as adoption deepens. Universities must therefore balance innovation with caution, ensuring that enthusiasm for new tools does not outpace responsible governance. Recognising the interdependence of technical, financial, ethical, and human factors positions institutions to harness AI's benefits in a sustainable and equitable manner.

In summary, this section has presented the cross-cutting themes linking both research questions. The barriers to AI adoption include limited skills and literacy, cultural resistance, weak technological infrastructure, financial constraints, and lack of strategy. The risks encompass academic misuse, data-privacy and security concerns, bias and ethics, reliability and oversight, and uncertainty around return on investment. The enablers comprise leadership commitment and vision, strategic planning and governance, infrastructure and data readiness, training and capacity development, phased implementation, and collaborative partnerships. Each of these dimensions was substantiated with participant quotations and analytical commentary.

The overall evidence indicates that GenAI can meaningfully support financial sustainability, but only within a supportive organisational ecosystem. Universities must simultaneously manage barriers, mitigate risks, and strengthen enablers to realise lasting impact. These findings complement the earlier analysis of cost, efficiency, and revenue by identifying the conditions under which such outcomes become achievable. The next chapter will synthesise these results with existing literature, offering theoretical interpretation and recommendations for institutional practice.

Chapter 5 conclusion

The findings presented in Chapter 5 demonstrate that senior university leaders view GenAI as a practical and strategic instrument for enhancing financial sustainability through two principal mechanisms: cost reduction and revenue generation. In relation to Research Question 1, the evidence indicates that AI is widely perceived as a means of reducing expenditure through automation, operational streamlining, and more efficient resource management. Participants consistently described how AI can help universities sustain or even improve service quality while containing or slowing the escalation of personnel and administrative costs. Addressing Research Question 2, the findings reveal that AI is equally regarded as a catalyst for revenue diversification and growth. This includes creating new offerings (such as AI-enabled short courses and digital products), optimising core income streams through improved student retention and fee recovery, and strengthening fundraising via data-driven engagement with alumni and partners. Collectively, these themes suggest that AI is not only a defensive tool for managing fiscal pressures but also a proactive lever for expanding institutional income sources.

Beyond these two central findings, Chapter 5 identified several cross-cutting factors that shape universities' capacity to realise AI's financial benefits. Participants emphasised that successful implementation depends on institutional readiness, leadership commitment, infrastructure adequacy, governance maturity, and the management of risks relating to ethics, privacy, skills, and organisational culture. These enablers and constraints apply equally to both cost-saving and revenue-enhancing initiatives, reinforcing that AI adoption represents a comprehensive organisational transformation rather than a purely technological intervention. The evidence therefore indicates that the financial outcomes associated with AI are contingent; achievable only when supported by deliberate strategic alignment, robust governance, and targeted investment in people and systems.

Together, the findings of Chapter 5 directly address the study's research questions and provide a grounded account of how AI is currently being interpreted, implemented, and experienced in South African universities. While participants recognise AI's potential to strengthen financial sustainability, they also acknowledge that this potential will not materialise automatically. It requires sustained leadership attention, organisational readiness, and effective change management. Chapter 6 now moves from description to interpretation, positioning these findings within the

broader body of academic and practitioner literature. It examines points of convergence and divergence with prior research, analyses the implications for policy and practice, and identifies how universities can strategically leverage GenAI to advance long-term financial resilience and sustainability.

CHAPTER 6: DISCUSSION OF RESULTS

This chapter interprets the study's findings, and outlines implications for practice and further research. The two research sub-questions, how GenAI can lower costs (RQ1) and increase revenue (RQ2) in South African universities, are examined using both the empirical findings presented in Chapter 5 and the existing literature reviewed in Chapter 2. The discussion outlines where the results align with or differ from earlier studies, showing the study's distinct contribution. It also considers the broader factors that shape GenAI's influence on university finances and the conditions required for its effective use. The chapter concludes by presenting practical recommendations for university leaders, highlighting future research opportunities, and offering final reflections on GenAI's role in supporting financial sustainability.

6.1 Cost management and efficiency (RQ1)

The first research question examined how GenAI can help universities reduce costs and improve operational efficiency. Chapter 5 presented themes of AI-driven cost savings and AI-driven operational efficiency gains, with examples such as automating administrative tasks, data-driven budgeting, and process optimisation. These findings closely support global studies that highlight AI's potential to make higher education operations more efficient. For example, Han et al. (2024) emphasise that AI can address inefficiencies in university financial management by automating routine processes and providing actionable insights for cost reduction (Han et al., 2024). Likewise, Kumar et al. (2024) emphasise GenAI's ability to transform administrative processes, allowing for more strategic financial planning and enabling institutions to "do more with less", a phrase that was also used by participants in this research. Interviewees frequently described AI as a way to sustain or even improve service quality without raising costs, supporting the view that GenAI can help universities operate more efficiently despite tight budget conditions. This alignment with prior studies indicates that the efficiency gains observed elsewhere are indeed applicable to the university context, contributing to literature on specifically examining AI during a systemic funding crisis in higher education.

A key finding was that automation helped reduce labour and operational costs, which participants viewed as one of the most immediate benefits of GenAI. This aligns closely with both industry analysis and previous research. For example, HolonIQ (2023) reported that AI technologies in education can automate large volumes of

administrative work, improving efficiency across departments. Our research provides real-world examples of this; interviewees mentioned deploying AI tools to handle repetitive tasks, tasks that would otherwise occupy staff for many hours. This practical evidence reinforces the claims of Verge AI (2025), which documented how AI systems can free up staff time by taking over routine processes like invoice processing and scheduling, thereby reducing overhead costs (Verge AI, 2025). One university CFO remarked that automating repetitive processes would allow staff to be “redeployed... to more important areas”, highlighting that AI can free people to focus on higher-value work rather than replace jobs altogether. Another participant pointed out that using AI tools internally could reduce reliance on external consultants, directly cutting those costs. These testimonies ground the literature’s efficiency arguments in tangible scenarios: they show how, in practice, GenAI is perceived as a way to trim labour costs (by automating both internal tasks and expensive outsourced functions) and reduce errors or delays that might carry financial penalties.

Beyond automation, participants highlighted analytics and data-driven decision-making as a mechanism for cost containment. GenAI and related AI tools can analyse large datasets (e.g. financial records, operational data) to identify wasteful expenditures or inefficiencies, guiding better budgeting and resource allocation. This finding resonates with the observations of Shoaib et al. (2024) and Mohsen et al. (2025). Shoaib et al. (2024), studying AI in the financial sector, found that AI systems minimise human error and streamline operations, outcomes equally applicable to university back-office functions. Mohsen et al. (2025) similarly suggest that AI-driven analytics can pinpoint inefficiencies and support more cost-effective operations in organisational settings. Our participants provided examples consistent with these insights; using AI to review procurement data for unnecessary spend, or to monitor utilities and maintenance logs to optimise resource use. By using AI’s pattern-recognition ability, universities can identify areas where costs can be reduced; for instance, spotting duplicate purchases, underused facilities, or processes that take up unnecessary time and resources. This ability to derive actionable intelligence from data is precisely what the literature foresees as an AI advantage. As one interviewee noted, an AI pilot processed thousands of student forms in about an hour. It saved staff time and surfaced a workflow bottleneck that could be removed, combining cost savings with process improvement. These results show how data-driven AI tools support “fine management” and cost-effective operations, as Han et al. (2024)

describe, who found that intelligent financial systems can redefine financial management by liberating personnel from routine tasks and reducing errors. In short, our findings confirm that AI can serve as a powerful cost-optimisation tool, validating predictions made in prior studies and reports about doing more with existing resources (Han et al., 2024; HolonIQ, 2023; Shoaib et al., 2024; Mohsen et al., 2025).

It is important to note that while the efficiency gains observed align with global trends, our research also addresses a gap in the literature regarding context. As discussed in Chapter 2, many global studies of AI in higher education or finance emphasise AI's promise but do not examine its use as a strategic solution for chronic financial shortfalls in universities (Kumar et al., 2024; Han et al., 2024). They often study isolated efficiency improvements rather than holistic financial sustainability impacts. Our research begins to fill that gap by focusing on South African universities amid a funding crisis. The evidence suggests that AI's known benefits in efficiency could indeed translate into meaningful financial relief when systematically applied to university operations.

However, interviewees also recognised that technology-driven savings alone may not resolve structural budget deficits. This aligns with literature cautioning that efficiency gains, while important, are not enough to address deeper funding challenges. Han et al. (2024) similarly observed that AI's role in broader financial sustainability remains poorly understood. This reflects a key insight; AI should form part of a wider strategy that also focuses on revenue growth (as discussed in RQ2) to have a real effect on financial sustainability (Motholo, 2023). Overall, the discussion on RQ1 shows a strong alignment between this study's qualitative findings and existing research. GenAI is broadly viewed as a tool for cost reduction and improved efficiency in universities, and this research provides context-specific evidence supporting that view. By automating routine work, minimising human error, and enabling smarter resource allocation, GenAI has the ability to help South African universities contain costs amid constrained budgets; affirming that institutions can "do more with less" through strategic use of AI (Kumar et al., 2024; Verge AI, 2025).

6.2 Revenue generation and diversification (RQ2)

The second research question explored how GenAI can support universities in generating new revenue or diversifying existing income sources. While managing costs is one part of financial sustainability, long-term stability also depends on

increasing income (Motholo, 2023). Consistent with this view, the findings showed that university leaders see GenAI not only as a cost-saving tool but also as an enabler of value creation and revenue growth. Chapter 5 highlighted a key theme of AI-driven revenue enhancement, with three related sub-themes: (1) diversification through new income streams beyond traditional funding, (2) optimisation of core revenue areas such as student success and pricing, and (3) stronger fundraising and partnerships. These insights align closely with recent literature emphasising that universities must “find new revenues (ideally both [cost efficiencies and revenue growth]) to survive and thrive” as traditional income sources decline (Motholo, 2023). In this section, we discuss each revenue-related theme in light of prior studies, showing that our participants’ ambitions for AI-driven revenue growth largely affirm the potential uses of AI identified by scholars; while also providing empirical depth to what has been, in literature, mostly a speculative discussion.

Diversification and new income streams: Participants in our research expressed considerable enthusiasm for using GenAI to create new offerings that could generate “third-stream” income (i.e. income beyond government subsidies and student fees). This aligns closely with the literature’s view that AI can help universities reinvent their programs and services. For example, our interviewees described ideas such as developing AI-powered products (like a locally relevant chatbot service or virtual laboratory simulations) that could be commercialised for other institutions or sold to external clients. They also mentioned offering new AI-centric courses and training programs (short courses, certifications in AI and data science) to attract professionals and additional fee-paying students. These findings are in strong agreement with the predictions of Saúde, Barros, and Almeida (2024) and Batista, Mesquita, and Carnaz (2024), who suggested that AI tools enable personalised and rapid content creation, allowing universities to launch online courses or micro-credential programs to tap into new markets of learners (Saúde et al., 2024; Batista et al., 2024). In Chapter 2 we noted that universities could use GenAI to generate educational content or simulations quickly, thereby expanding offerings for professionals or international audiences. Our study’s participants are actively considering exactly such strategies; for instance, using AI to develop short learning programs on emerging tech skills, or creating virtual lab experiences that can be licensed to schools lacking physical labs. This provides empirical confirmation that what was described as a hypothetical opportunity in literature is being taken seriously by practitioners.

Moreover, the findings reflect an innovative mindset, with universities using their internal AI expertise (both researchers and technical staff) to develop marketable solutions. Hannan and Liu (2023) note that AI is becoming a key differentiator between institutions, allowing those that adopt it to innovate in programme design and student experience. This research provides clear examples of that trend; some universities are exploring ways to sell AI-based services, such as consulting for industry or applications for government, as part of their efforts to stand out and generate new income streams. This aligns with Hannan and Liu's (2023) argument that such innovation can attract funding and strengthen institutional competitiveness. Similarly, George and Wooden (2023) suggest that AI-enabled innovations in programmes and services can enhance a university's appeal to both students and funders. The entrepreneurial initiatives mentioned by our interviewees (like developing spin-off companies or patenting AI tools from university research) resonate with this; by capitalising on GenAI-related intellectual property, universities can potentially draw investment and generate royalties, thereby strengthening their financial base while also boosting their reputation as innovative institutions.

Optimising core revenue (student success and pricing): Another important area of revenue growth highlighted by participants was strengthening existing income sources, particularly tuition fees and government subsidies linked to student performance. The findings suggest that university leaders view GenAI as a means to improve student recruitment, retention, and success; factors that have a direct impact on revenue. This view is well supported in the literature; for example, previous studies show that AI-driven analytics can personalise marketing to prospective students and identify those at risk of dropping out, allowing for early intervention that improves enrolment and completion rates (Saúde et al., 2024; Batista et al., 2024). In this research, one university executive described using AI to flag students who are academically at risk and trigger early support, with the explicit aim of improving graduation rates; knowing that better student success translates into higher subsidy income (since government funding is often linked to completions). This real-world application directly mirrors what Saúde et al. (2024) found; that AI can indeed help “personalise support for students, thereby improving retention and completion” (paraphrased, Saúde et al., 2024). By increasing the number of students who graduate, universities secure more of the performance-based government subsidies and also avoid losing tuition from dropouts. Similarly, participants noted using AI in recruitment (profiling applicants to identify those most likely to succeed and

graduate) which aligns with the goal of improving student cohort quality and minimising dropout-related revenue loss. This practice finds support in the literature as well; even though it's a newer concept, it ties into the broader theme of data-driven decision-making in enrolment management. Farrelly and Baker (2023) discuss GenAI's impact on higher education practice and mention that AI can enhance outreach and student support, indirectly contributing to financial health by improving institutional reputation and student success (Farrelly & Baker, 2023). Our findings demonstrate this in practice. Targeted outreach to prospective students (using AI to identify suitable candidates) and targeted support for current students (using AI-based early warnings) both show how the technology can translate into financial gains by improving student success and protecting tuition income.

Participants also discussed dynamic pricing and revenue management for non-traditional programmes as another way AI could optimise income. Universities in South Africa have limited scope to raise tuition fees for degree programmes due to regulatory and affordability constraints. However, for areas such as executive education, online learning, and certificate courses, they can adjust prices more freely. One finance manager suggested applying AI to analyse market demand and competitor pricing to determine optimal fees for short courses, even adjusting them in real time as demand changes. This approach resembles revenue management models used in sectors like aviation and hospitality and represents a more advanced method for increasing income per student in these offerings. Although dynamic pricing was not explicitly covered in the reviewed literature, it aligns with the broader concept of AI-enabled decision support in financial planning. By scanning large datasets on enrolment trends and willingness-to-pay, AI can recommend pricing strategies that increase revenue without significantly shrinking enrolment. This finding extends the literature by introducing a concrete example of AI's application in financial strategy optimisation at universities; an area that hasn't been deeply explored in prior academic work but makes intuitive sense given AI's strengths in data analysis.

Another key revenue challenge for South African universities is student fees and unpaid debt. Many students are unable to pay their fees in full, resulting in large outstanding balances on institutional accounts (Whitelaw et al., 2023). Participants suggested that AI could play a role in improving fee collection and debt management. For instance, AI analytics could predict which students are at risk of defaulting and

enable early interventions such as payment plans, outreach, or bursary offers. It could also segment students according to the most effective communication approach to encourage payment. One CFO observed that even a small increase in collections would benefit the university's finances, and that AI could help tailor strategies; some students respond to reminders, while others require a different approach.

This type of predictive and adaptive use of AI is well established in the banking sector and applying it to tuition collection represents an innovative crossover. Although the academic literature on higher-education finance has not explored this in detail, it aligns with Shoaib et al.'s (2024) work in financial institutions, which shows that AI enhances credit-risk evaluation and operational efficiency. By reducing bad debt through predictive analytics, universities can retain more of their billed income. In addition, identifying financially distressed students early allows for supportive action before debt escalates, reflecting the social-responsibility dimension of university management.

In essence, our findings on AI-aided revenue optimisation demonstrate that universities are adopting a business-minded approach, using technology to enhance what is essentially customer relationship management (for students as customers) and financial analytics for core operations. This confirms and extends literature suggestions that AI's data capabilities can be leveraged to improve existing income channels (Farrelly & Baker, 2023; Saúde et al., 2024).

Enhanced fundraising and partnerships: The third revenue-related theme identified in the findings focuses on the use of AI to grow income from donations, grants, and partnerships. Participants explained that GenAI and data analytics can support this by identifying potential donors (particularly within large alumni databases) personalising donor communication, linking researchers to relevant grant opportunities, and improving the management of partnerships. Although research on AI in higher-education fundraising remains limited, emerging evidence suggests that the technology could have a notable impact in this area. As discussed in Chapter 2, GenAI can enhance alumni engagement by generating personalised messages and outreach materials (Farrelly & Baker, 2023). The findings from our research provide a clear illustration of that potential. For instance, one interviewee explained that AI tools can be used to “mine the alumni database to find who's most likely to give, and even tailor messages to them”. This approach is a concrete realisation of what

Farrelly and Baker (2023) anticipated; using AI to segment and engage donors more efficiently. By examining past donation patterns and donor profiles, AI can help fundraising teams prioritise alumni or supporters with a higher likelihood of giving and craft messages that align with their interests. Participants confirmed that this approach often leads to higher response rates and, in some cases, larger donations, thereby strengthening fundraising results.

In addition, AI was viewed as valuable for developing corporate partnerships and securing grants. Interviewees referred to tools that can search for research funding calls or identify potential industry partners interested in specific projects. This proactive matching process has traditionally relied on personal networks or manual searches, but AI allows it to happen at scale. In practice, a research office could use AI to track funding databases and alert academics to relevant grant opportunities, or to pinpoint companies whose priorities align with the university's research expertise. By enabling these connections, AI contributes to attracting research and partnership income; such as industry-funded projects, endowed programmes, or technology transfer agreements.

Although this application of AI has not been widely discussed in higher-education research, it aligns with the broader principle of data-driven opportunity identification that AI performs well. It also connects to Kurien and Soglo's (2024) observation that African universities have yet to apply AI extensively in non-academic areas; here, they are beginning to do so through partnership and advancement initiatives.

In summary, the discussion of RQ2 indicates strong alignment between this study's findings and emerging scholarship on AI's contribution to revenue generation in universities. Participants' perspectives on using GenAI to create new offerings, enhance student success, apply dynamic pricing, and strengthen fundraising efforts reinforce the potential pathways outlined in the literature (Saúde et al., 2024; Hannan & Liu, 2023; Farrelly & Baker, 2023). What this research adds is an empirical verification that these avenues are being actively explored by university leaders in a specific, challenging context. This helps move the conversation from theoretical possibility to practical probability. It's worth noting that much of the literature so far has been speculative or based on early pilots when it comes to AI in higher education finance. By providing evidence from decision-makers on the ground, our research begins to ground those speculations in reality; showing which ideas have traction and what considerations are arising (for example, the strong emphasis on student

success and fundraising in our findings suggests those may be seen as more immediately feasible or impactful than some might have expected, whereas the literature treated all possibilities somewhat equally). The combination of cost-focused and revenue-focused applications of GenAI, as undertaken in our research, contributes to a comprehensive approach to financial sustainability that is consistent with the fundamental need for universities to both “find new efficiencies [and] new revenues” (Motholo, 2023).

The analysis of RQ1 and RQ2, our findings suggest that GenAI holds significant promise on both sides of the financial equation for universities. It can help reduce or optimise costs, and it can also bolster and diversify revenue. This dual impact is particularly significant for South African public universities, where, as Chapter 2 outlined, declining state funding and rising costs have drained budgets severely (Whitelaw et al., 2023; Motholo, 2023). GenAI is not a silver bullet (savings and new income will take time to materialise and require investment) but it represents a new strategic tool in the arsenal of university management. Importantly, our discussion also highlights that successfully reaping these benefits is conditional on certain cross-cutting factors, which we discuss next.

6.3 Cross-cutting factors: enablers and barriers to implementing GenAI

While the potential benefits of GenAI for cost savings and revenue generation are evident, both our findings and the literature make it clear that realising these benefits depends on crucial enablers and overcoming barriers. Chapter 5 showed that participants repeatedly mentioned factors such as institutional capability, data readiness, governance requirements, risk management, and broader organisational conditions that influence the impact of AI. These cross-cutting themes align with existing literature on AI adoption in higher education, particularly within developing-country contexts (Kurien & Soglo, 2024; Butcher et al., 2021). This section reflects on how participants in this research understood these enablers and challenges, linking their views to insights already established in the literature.

Digital infrastructure and data readiness: A recurring theme in the interviews was the need for strong IT infrastructure and reliable, high-quality data for GenAI initiatives to succeed. University leaders emphasised that AI systems are only as effective as the data they use and the technology environment that supports them. If financial data is incomplete or siloed in legacy systems, or if the university lacks computing

power and connectivity, AI tools will have limited utility. This concern is strongly supported by prior studies. Kurien and Soglo (2024) found that many African universities face inadequate digital infrastructure and bandwidth, which hinders sophisticated AI deployment (Kurien & Soglo, 2024). Butcher et al. (2021) also observed that outdated systems and weak data management capabilities in sub-Saharan Africa create major obstacles to realising the benefits of new technologies. The experiences shared by our participants reflect this reality. Several noted challenges in integrating AI tools with existing financial systems and emphasised the need to invest in modern data warehouses or cloud platforms to support AI processing. They also raised concerns about data quality; for instance, when student or financial records are poorly maintained, predictive analytics for student success or cost management become unreliable. The key implication, therefore, is that universities need to strengthen their digital infrastructure and prioritise data integrity as a critical foundation for GenAI initiatives. This is not an insignificant undertaking given resource constraints, but without it, AI efforts could fail or produce flawed insights. The literature and our findings together stress that technology alone doesn't solve problems; it must be supported by good data and systems. In positive cases, participants who had access to better infrastructure (for example, one university piloting an AI tool had recently centralised their data and moved to a cloud-based ERP) reported much smoother implementation and more convincing results. This indicates that closing infrastructure gaps is both essential and worthwhile, as it allows institutions to make full use of GenAI's capabilities.

Human capital and skills: In addition to technical infrastructure, human capability emerged as a crucial factor. Many interviewees pointed out that integrating GenAI into university management requires staff who understand how to use these tools effectively; both in implementation and in interpreting their outputs. There is a need for data analysts, AI specialists, or at least training for existing finance and IT personnel to work effectively with AI. This reflects a well-known challenge identified in the literature; a shortage of skilled personnel in AI and data science within higher education (Butcher et al., 2021; Kurien & Soglo, 2024). Butcher et al. (2021) noted that many African universities lack the skilled personnel needed to implement and maintain AI systems. Our findings confirm that this concern remains prominent among university leaders. Several participants reported challenges in attracting or retaining data scientists due to budget constraints and competition from the private sector. Others explained that they depend on external consultants or vendors for

initial AI projects but are concerned about sustaining internal capability over time. The implication is that universities should invest in dedicated capacity-building initiatives (such as training administrative staff or partnering with computer science departments) so that the expertise to manage GenAI solutions becomes part of the institution itself. One particularly useful insight came from a participant who proposed forming cross-functional teams (combining finance, IT, and academic staff) to oversee AI projects, ensuring that both technical and domain knowledge are represented. This kind of internal collaboration could mitigate the skill gap by pooling expertise. In any case, our findings echo the literature's message that without investing in human capital, AI initiatives could stall. GenAI tools are not plug-and-play solutions; they require knowledgeable oversight. Therefore, developing a workforce that is AI-literate is a key condition for successful implementation.

Leadership, strategy, and governance: Another strong theme was the need for visible leadership support and clear institutional strategies and policies to guide the use of AI. Participants emphasised that introducing AI can be disruptive and may face resistance; for example, from staff who fear automation or from decision-makers uncertain about trusting AI-generated outputs. Leadership therefore plays a critical role in championing AI initiatives, allocating resources, and framing a shared vision that positions AI as a tool to enhance, rather than replace, human capability. This reflects Kurien and Soglo's (2024) finding that the absence of clear strategies or leadership commitment in African universities contributes to hesitation and slow adoption. In this research, institutions with explicit digital transformation plans were further advanced in experimenting with AI, while those without such strategic direction showed greater caution.

Governance also emerged as an essential factor, encompassing policies on the ethical use of AI, data privacy, and accountability. Interviewees expressed concern about data security (particularly when handling sensitive financial or student information) and about potential ethical risks, such as AI unintentionally influencing which students are flagged for support. These issues mirror broader debates in the AI literature, even if not focused specifically on higher education finance. The implication is that universities should establish frameworks or guidelines for ethical AI use, drawing from emerging best practices and relevant legislation. Several participants mentioned compliance with South Africa's POPIA and the need to ensure that all AI systems meet those requirements. Establishing clear governance

mechanisms can strengthen stakeholder confidence, ensure regulatory compliance, and remove barriers to implementation.

Equally important are cultural and change management considerations. The introduction of GenAI requires deliberate communication, staff engagement, and training to ensure that employees view the technology as a support rather than a threat. One participant noted that although some staff were initially sceptical about an AI tool that automated part of their work, their perceptions shifted positively after realising it reduced workload and allowed them to focus on more meaningful tasks. This demonstrates that how AI is introduced matters. Leadership must consistently communicate that GenAI is intended to enhance productivity and enable staff to concentrate on higher-value responsibilities, rather than simply reduce headcount. Combining this message with staff involvement (such as pilot projects where end-users provide feedback) can turn potential resistance into genuine buy-in. Again, this echoes general technology adoption literature; human acceptance is as important as technical efficacy.

External environment and policy: Finally, it is important to recognise the influence of the external environment. Universities do not operate in isolation; government policy, funding incentives, and the broader technology ecosystem all shape how AI is adopted. In South Africa, there is increasing government attention on the Fourth Industrial Revolution, yet specific policies and funding mechanisms for AI in higher education are still developing. Several participants expressed hope that departments such as Higher Education and Science & Innovation might establish grants or programmes to support digital transformation across universities. Should such support become available, it would likely accelerate AI implementation; without it, institutions remain largely dependent on their own limited resources.

The literature also points to underdeveloped regulatory frameworks for AI (Kurien & Soglo, 2024), which can act as a double-edged sword. On one hand, fewer restrictions may allow flexibility and experimentation; on the other, the lack of clear guidance can create uncertainty. Some universities hesitate to proceed without explicit rules governing issues such as data protection or the ethical use of AI, fearing potential backlash if automated decisions are viewed as unfair. Our findings show that university leaders are proceeding cautiously in part because of this uncertainty. One participant mentioned waiting for clearer guidance from authorities before applying AI in student-related decisions to ensure ethical compliance. This highlights

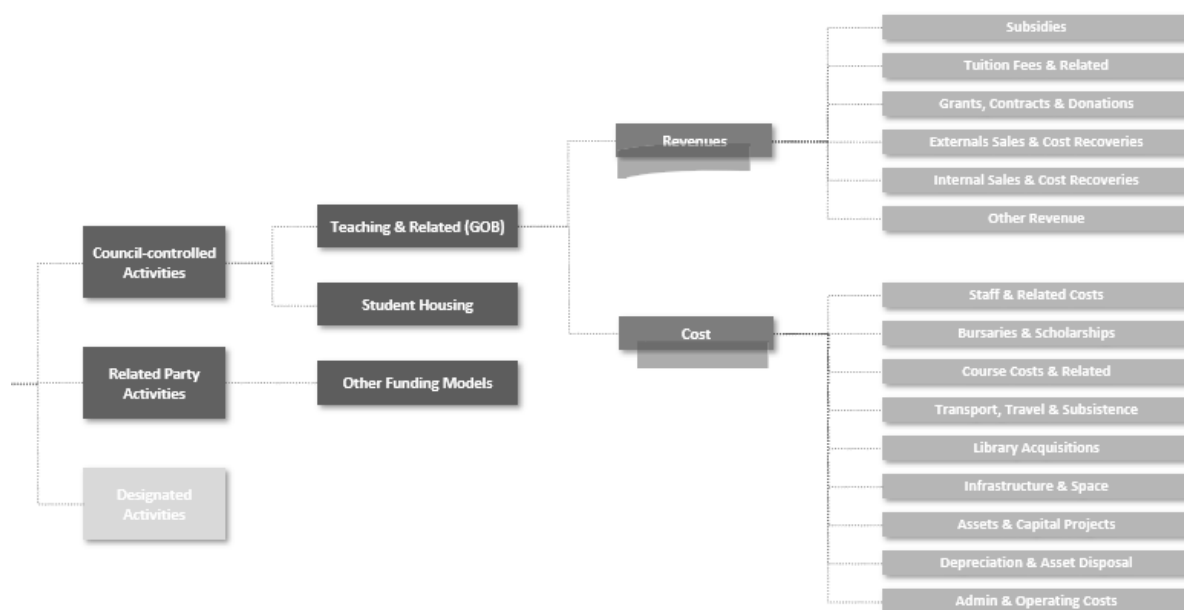
the need for ongoing dialogue between universities, policymakers, and regulators to establish norms and frameworks that promote responsible AI use.

In summary, this research demonstrates that integrating GenAI into university financial management is not solely a technical exercise but a socio-technical process. Successful adoption depends on multiple enabling conditions (robust infrastructure, reliable data, skilled personnel, committed leadership, and sound governance policies) working together. These results echo the broader literature on the challenges of technology adoption in African higher education (Butcher et al., 2021; Kurien & Soglo, 2024) while providing richer insight into how these issues play out in everyday institutional contexts. Encouragingly, participants did not view these challenges as deterrents but as obstacles to be addressed. Their willingness to invest in systems, build staff capability, and develop AI policies suggests a proactive and pragmatic stance. While GenAI is not a cure-all for financial constraints, with the right foundations it can become a powerful instrument for strengthening financial sustainability. The next section builds on this understanding to offer concrete recommendations for practice.

6.4 Conceptual model

6.4.1 University financial structure: foundation for the conceptual model

Before presenting the integrated GenAI financial sustainability conceptual model, it is important to contextualise the financial environment in which South African universities operate. University income and expenditure are categorised into a defined set of cost and revenue line-items that form the foundation of strategic planning, budget allocation, and performance reporting. The following diagram presents a typical university finance structure, encompassing both council-controlled and related-party activities that contribute to two main financial pillars: revenue and expenditure. Revenue is largely generated through tuition fees, government subsidies, grants, partnerships, and commercial ventures, while Cost is primarily driven by staffing costs, infrastructure operations, student support, and core academic delivery.



Cost & Revenue Attributes: Developed from Multiple Universities' Financial Statements

This diagnostic mapping is not included for description alone; it establishes the financial baseline against which GenAI capabilities are assessed in this study. The conceptual model developed in the following section directly builds on this structure, demonstrating how each GenAI capability aligns with, influences, or transforms one or more of these financial line items. In doing so, the model provides a practical and evidence-based mechanism for understanding how GenAI can shift institutional financial trajectories from cost escalation and revenue stagnation to optimisation, innovation, and long-term sustainability.

South African universities are no longer facing a short-term financial strain, but a systemic and structural crisis (University D, 2019). Incremental cost controls and fragmented revenue initiatives are no longer sufficient. Achieving financial sustainability now requires a fundamental shift; one that moves beyond traditional levers and embraces transformative mechanisms capable of reshaping the long-term financial trajectory of universities.

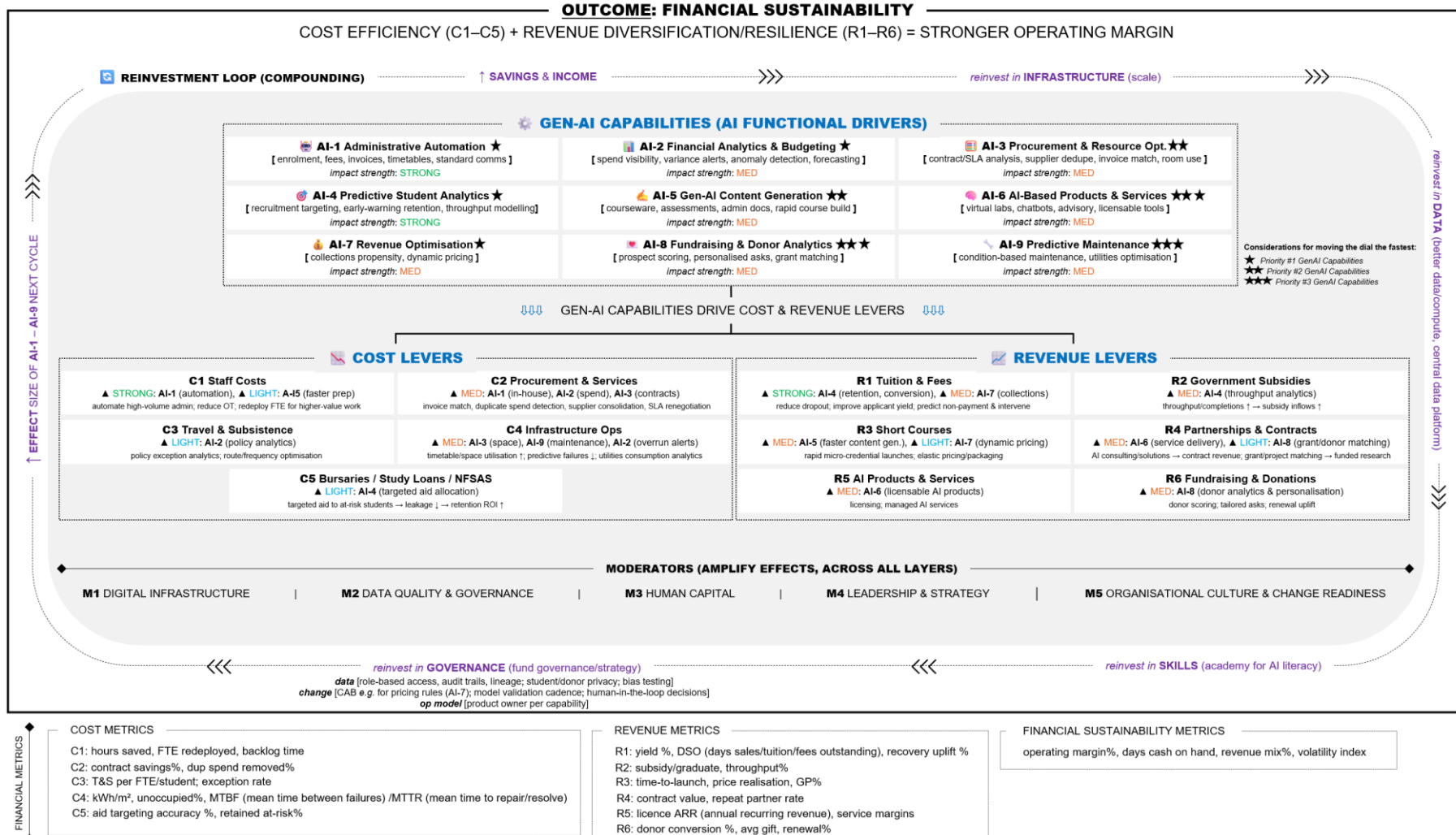
The rise of GenAI offers such a transformation. It should not be viewed as a mere technological add-on but as a strategic financial tool that can restructure cost bases, unlock new revenue streams, and enable reinvestment cycles that generate compounding value over time. Yet, despite the rapid progress of GenAI, the literature highlights a notable gap; there is currently no framework that systematically links GenAI capabilities to university financial levers in a way that is both actionable and

measurable, and that aligns with the standard budget line items used in South African higher education financial planning and reporting.

Drawing on the empirical findings of this study and integrating insights from both global and local scholarship, this research develops an integrated conceptual model. The model shows how specific GenAI capabilities connect directly to cost-reduction and revenue-generation mechanisms, and how these, in combination, contribute to the financial resilience of universities. This model moves beyond theoretical speculation by grounding each linkage in actual institutional challenges and stakeholder perspectives, thereby offering a practical, evidence-based blueprint for financially threatened universities to transition toward long-term sustainability.

The following section introduces this conceptual model in full, illustrating not only the directional relationships between GenAI capabilities and financial outcomes, but also the moderating conditions, strength of impact pathways, and reinforcement loops that determine the extent to which value is realised or eroded.

6.4.2 Conceptual model: The GenAI-Driven Financial Sustainability Model for South African Universities



Generative AI capabilities (top of model)

The model's top layer lists the GenAI capabilities (AI functional drivers) that fuel all downstream effects. For instance, AI 1: Administrative Automation applies AI to handle routine administrative tasks such as invoicing and form processing. This reduces staff effort (removing manual admin, cutting overtime) and frees up employees for higher value work (Verge AI, 2025). AI 2: Financial and Spend Analytics involves models that analyse expenditure patterns and flag irregularities such as duplicate invoices or policy exceptions. This drives more accurate budgeting and procurement, cutting waste. AI 4: Student Analytics (early-warning systems) predicts at risk students and optimises enrolment/retention (Verge AI, 2025), boosting tuition and subsidy income. AI 5: Content Generation (for example, course or material authoring tools) significantly accelerates the development of curricula and learning resources. AI 6: AI Products/Services refers to building AI-based products or consulting to sell externally. AI 7: Revenue Optimisation (dynamic pricing, collections) uses AI to improve enrolment yield, recovery and pricing strategies. AI 8: Donor/Fundraising Analytics applies predictive models to score donors and personalise asks. AI 9: Predictive Maintenance monitors equipment/facilities to reduce downtime and energy use. In summary, each capability (AI 1...AI 9) is a financial lever tied to specific cost (C1–C5) or revenue (R1–R6) lines.

- *AI-1 Admin Automation:* Automates high volume tasks. Cuts C1 (Staff) costs and C2 (Procurement) overhead by reducing manual labour and outsourcing.
- *AI-2 Financial Analytics:* Data analytics on budgets/spend. Reduces C2–C4 costs by identifying duplicate or unauthorised expenditure and flagging potential budget overruns.
- *AI-3 Procurement/Resource:* Intelligence on suppliers, contracts and space. Improves C2 (procurement efficiency) and C4 (space/utilities) by better negotiating terms, scheduling, and utilisation.
- *AI-4 Student Analytics:* Predicts student outcomes. Increases R1–R2 (tuition/subsidy) by improving admissions yield and retention (raising graduation rates); also targets C5 (bursary) spending to those who need it most.
- *AI-5 Content Gen:* Automated content and curriculum creation. Expands R3 (short-course revenue) by cutting course development time (micro-credential launches) and lightening faculty prep burdens.

- *AI-6 AI Products/Services*: Develop or offer new AI tools and managed services. Supports R4–R5 (partnerships and AI-related product revenue) by creating income streams such as licensing and consulting.
- *AI-7 Revenue Optimisation*: Smart pricing and automated collections to enhance R1 (tuition) and R3 (short courses) through proactive billing, dynamic pricing, and improved recovery rates.
- *AI-8 Donor Analytics*: Predictive modelling to fundraising, increasing R6 (donations) and R4 (sponsored research) by identifying high-potential donors and tailoring renewal requests.
- *AI-9 Predictive Maintenance*: Sensors and analytical models to manage facilities proactively, reducing downtime and avoiding costly repairs. Reduces C4 (infrastructure) costs via condition-based maintenance (cutting energy use and unplanned downtime).

Each capability is interpreted on the diagram to the specific cost/revenue lines it affects.

Cost levers (left of model)

The left side of the model shows cost categories (C1–C5) that AI can shrink. In each case, GenAI capabilities inject efficiency into budget lines:

- *C1 Staff & Admin Costs*: This includes salaries, overtime, etc. AI automation (AI 1) directly cuts C1 by eliminating routine work (chatbots answering FAQs, auto-processing forms). Less human labour is needed, so FTEs are redeployed to mission-critical work. Research indicates that AI-driven automation can lower administrative costs in higher education by as much as 30% (Verge AI, 2025).
- *C2 Procurement & Services*: Expenditure on supplies, contracts, and outsourced services. AI analytics (AI 2/3) help lower C2 costs by detecting duplicate or low-value spending and supporting better supplier negotiations. For instance, invoice-matching and supplier scorecard models can identify inefficiencies and eliminate waste. Finance/HR AI tools (financial forecasting, RPA) also improve budgeting and cut processing costs.
- *C3 Travel & Subsistence*: Travel reimbursements, conferences, transportation. AI can reduce C3 costs by analysing travel policies and optimising travel routes and frequencies. Though not detailed on the slide, similar analytics flag excessive travel and enforce compliance.

- *C4 Infrastructure (Facilities/Ops)*: Utilities, space, and maintenance costs. Predictive maintenance (AI 9) and space or timetabling optimisation (AI 3) reduce C4 costs by identifying underused buildings, improving energy efficiency, and scheduling maintenance only when required. Dynamic scheduling combined with sensor data further lowers utility and repair expenses.
- *C5 Bursaries & Scholarships*: Expenditure on student financial support. AI 4 Student Analytics improves C5 efficiency by identifying at-risk students early and directing aid to those most likely to continue their studies. This reduces leakage (where aid is allocated to students who drop out) and increases retention, enhancing the return on bursary investment.

Each cost lever therefore has specific AI mechanisms tied to it. Overall, combining these AI interventions improves operating efficiency across the balance sheet.

Revenue levers (right of model)

The right side shows revenue lines (R1–R6) that AI capabilities can grow. In essence, GenAI enables higher revenues or new income:

- *R1 Tuition & Fees*: Net tuition income per student. AI 4 (student analytics) and AI 7 (collections/pricing) raise R1 by improving enrolment yield and reducing dropout. For example, better personalised recruitment boosts admission rates, and predicting non-payment allows early interventions.
- *R2 Government Subsidy*: Public funding tied to graduations. With AI 4 improving graduation throughput, universities receive higher subsidy income per student. The model highlights this relationship as “↑ completions drive subsidy”.
- *R3 Short-Course & Other Program Income*: Revenues from micro-credentials or executive courses. AI 5 (content gen) and AI 7 (dynamic pricing) accelerate course development and optimise pricing, increasing this revenue stream. For instance, rapidly launched online courses and elastic pricing can significantly lift short-course yield.
- *R4 Partnerships & Contracts*: Income from industry partnerships or sponsored research. AI 6 (AI services) builds this by creating new consulting products and aligning research grants (e.g. AI-driven project matching).
- *R5 AI Products/Services (New Income)*: Sale of AI-based software or managed AI services. Driven primarily by AI 6, this lever generates additional income through

licensing, subscriptions, or consulting. It represents a growth opportunity unique to institutions that develop and manage AI capabilities internally.

- *R6 Fundraising & Donations*: Gifts and alumni giving. AI 8 (donor analytics) boosts R6 by scoring donors and personalising appeals. For instance, predictive models can identify high-potential donors, while AI-generated personalised appeals enhance engagement and response rates. The model explicitly links AI 8 to R6.

Together, these AI-driven revenue levers diversify and strengthen income streams. Importantly, every rand gained via R1–R6 directly improves financial sustainability.

Financial outcome (top of model) and reinvestment (circling the model)

At the top of the diagram is the Financial Sustainability outcome. In formulaic terms, it's (total cost savings + total revenue uplifts) minus AI investments. Practically, this means the net impact of all AI levers is measured as an improvement in operating margin, cash on hand, and revenue mix:

Outcome =

$(\sum \text{cost savings } C1-C5 + \sum \text{revenue uplifts } R1-R6) - (\text{AI capex/opex} + \text{readiness cost})$

Put simply, we add up the reduced spending from C1–C5 and extra income from R1–R6, then subtract the costs of implementing AI. The model shows this resulting in a stronger operating margin and more days cash on hand.

A central feature of the model is the reinvestment loop that connects capabilities and financial levers. This loop shows how savings and new income are reinvested into AI capabilities and infrastructure, creating compounding benefits over time. For example, early cost savings can be redirected to upgrade data platforms (M1) or expand analytics teams (M3), leading to even stronger outcomes in subsequent cycles. The model incorporates three interrelated feedback loops:

- *Efficiency Loop*: Savings generated through automation and analytics (AI 1/2/3/9) are reinvested to fund additional AI initiatives, further reducing costs.
- *Growth Loop*: New revenue from content creation, services, and donor engagement (AI 5/6/8) is used to strengthen governance and accelerate scaling into emerging areas.

- *Retention Loop*: Improvements from student analytics (AI 4) free up resources for investment in data systems and talent (M1/M3), which in turn enhance enrolment and student retention.

These feedback loops ensure the model isn't one off; each round of AI-driven benefit fuels the next. Overall, both these elements (outcome, reinvestment) tie everything together; effective AI use grows margins today and through compounding effects tomorrow.

Moderators (bottom of model)

Anchoring the entire model are the moderators that influence all elements. These represent the organisational capabilities required for any of the preceding levers to deliver value:

- *M1 Digital Infrastructure (Data Pipelines, Compute, Identity/Access)*: Forms the technological and security foundation. Without reliable data pipelines and sufficient computing capacity, many AI initiatives (such as administrative automation, student analytics, and predictive maintenance) cannot operate effectively at scale.
- *M2 Data Quality & Governance*: High-quality, well-integrated data is essential. Accurate analytics and AI models depend on clean, verified datasets; poor data quality can undermine forecasts and donor scoring accuracy.
- *M3 Human Capital (Skills & Capacity)*: Refers to trained personnel such as data engineers, AI/ML (machine learning) specialists, and product owners. Even the most advanced AI systems require skilled staff to design, validate, and maintain them. Model pipelines and workflows need continuous oversight and refinement.
- *M4 Leadership & Strategy*: Includes clear priorities, budgets, and governance frameworks. Strong executive backing directs resources to high-impact projects, while strategic vision ensures that AI initiatives remain aligned with financial objectives.
- *M5 Organisational Culture & Change Readiness*: Involves fostering an innovation-oriented culture where staff are encouraged and equipped to adopt AI tools. Without buy-in and appropriate incentives, even effective solutions may go unused. Structured change management ensures that staff actively apply AI insights to improve processes.

These moderators effectively govern the return on investment (ROI) of the model. Gaps in infrastructure, skills, or governance can slow down, or even derail, otherwise high-

potential AI initiatives. In the model, they are depicted as involving all layers, illustrating that success depends on these enablers.

Implementation pathways, metrics, and risk considerations

The model is deliberately non-linear in its implementation guidance. It steers clear of a fixed “one-size-fits-all” timeline in favour of adaptive sequencing. Universities may adopt a portfolio approach: simultaneously pursuing quick-win pilots while laying groundwork for larger initiatives. For instance, a campus facing severe budget constraints might begin by implementing administrative automation and improving accounts receivable processes; quick-win initiatives that generate immediate cash flow. As part of this short-term focus, it could also prioritise data hygiene (M2) and a basic change control process. In contrast, a university with stronger IT capabilities might start with student retention analytics or AI-supported short-course development, taking advantage of its existing data platform. In all cases, projects are chosen to match institutional maturity; a data-poor university will begin by cleaning and integrating finance data (addressing M2), while a digitally advanced university could immediately launch advanced chatbots or predictive models. The key is balancing short-term operational gains against building the digital and human capacity for scaling GenAI (consistent with the model’s portfolio philosophy).

Success is measured using specific key performance indicators (KPIs) linked to each financial lever. For cost reduction projects, metrics might include hours saved per staff FTE, backlog cycles time, or percentage of overtime cut for administration (C1); for procurement analytics (C2) one might measure contract savings and duplicate spend removed; for infrastructure (C4), metrics like kWh per square meter or unoccupied space percentage. On the revenue side, useful KPIs include enrolment yield or retention rates (R1/R2), short course enrolment growth (R3), and donation/grant increases (R6). In practice, every element in the model can be linked to a measurable output (e.g. % of invoices auto-approved, savings per trip booked, etc.) to “prove the model”.

Risk is managed by the same enablers; poor data, legacy systems, or insufficient governance can reverse gains. The model explicitly flags these risks as “gates” to ROI. For example, deploying a predictive maintenance tool without energy usage data (M2) or network capacity (M1) would be ineffective. Likewise, without leadership championing AI projects (M4) and incentives for staff to adopt new tools (M5), even the best applications may languish end up as “AI theatre”. Therefore, the model advises that risk mitigation

(upgrading infrastructure, training staff, establishing AI governance frameworks) should proceed in tandem with use-case pilots.

Theoretical implications and connection to research questions

The proposed model contributes theoretically by integrating insights from technology adoption and financial management. As noted in the introduction, there is a gap in linking GenAI to organisational financial strategy. This model fills this gap by mapping GenAI capabilities explicitly to cost-containment and revenue-generation levers. In doing so, it extends digital transformation theory (showing how a general-purpose AI technology reconfigures cost structures and income sources) and organisational innovation theory (by highlighting the role of enablers and feedback loops in complex public institutions such as the studies universities). The model therefore offers a basis for future research; it can be tested empirically (e.g. by measuring KPIs in pilot projects) and compared across contexts, enriching interdisciplinary literatures on higher-education management, IT governance, and resource-constrained innovation.

Importantly, every element of the model ties back to the core research questions. By explicitly framing each AI intervention in terms of cost lines and revenue streams, the model shows how GenAI can be leveraged to improve university finances. The linkage is direct; efficiency-focused capabilities (e.g. AI-driven automation and analytics) drive down operational costs (addressing RQ1), while growth-oriented capabilities (e.g. AI-supported short courses, donation analytics, new AI products) improve income (addressing RQ2). In summary, the GenAI-Enabled Financial Sustainability Model for South African Universities provides a cohesive, empirically grounded pathway for deploying AI in higher education; encapsulating the findings into a coherent story that answers the main RQ: GenAI can help South African public universities achieve financial sustainability by systematically cutting costs and cultivating new revenues.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

This research set out to explore whether GenAI could help South African public universities tackle their financial crisis. The context: government subsidies have stagnated (an increase of just 0.9 percent in 2023/24), enrolments continue to rise, and operational costs (especially staff and energy costs) often exceed sustainable levels. Universities collectively hold about R16.5 billion in unpaid student fees. Under such strain, new solutions are needed to maintain educational quality and widen access. Meanwhile, AI tools that can write text, analyse data and generate content are transforming industries worldwide. Leading experts argue that many university processes are “ripe for GenAI” automation (Williams, 2025). Yet no prior research had examined GenAI as a financial strategy for South African universities. By investigating this question, the research makes a timely contribution to both scholarship and practice.

The research adopted a qualitative, exploratory approach. Semi-structured interviews were conducted with senior university leaders (including finance and technology executives) to gain detailed insights into how GenAI can support cost reduction and revenue growth. The data were analysed thematically, enabling the identification of shared themes and patterns. Together, the findings present a comprehensive view of how university decision-makers perceive GenAI’s role in financial strategy. Importantly, the research revealed that stakeholders recognise strong potential in GenAI for streamlining operations and improving efficiency, as well as for driving innovation in revenue generation. However, this optimism is tempered by concerns about institutional readiness and implementation challenges. These findings were synthesised to address the research questions and highlight the broader significance of the study.

7.1 What was studied and why it matters

The research explored how GenAI can reduce costs and generate new revenue within South Africa’s public universities. Specifically, it asked: (1) How can GenAI be used to cut operational costs and improve efficiency? (2) How can GenAI be applied to enhance and diversify revenue streams? These questions are important because traditional funding models are no longer sufficient. Universities cannot continue increasing tuition fees without risking social unrest, while government budgets remain under pressure. If GenAI can automate routine work, eliminate waste, attract new students, or enable new service offerings, it may provide a practical route to financial sustainability. Exploring these

possibilities is crucial for the continued survival of public universities, which play a central role in national development and social mobility.

7.2 Research context and Its importance

The research took place in the context of South Africa's higher-education funding crisis. Public universities operate within a system of limited state subsidies, high student debt, and escalating costs. The financial pressure is amplified: staff costs often consume more than half of university budgets, yet universities are also expected to broaden access for historically disadvantaged groups. At the same time, the Fourth Industrial Revolution discourse encourages institutions to adopt advanced digital technologies. GenAI stands out because it promises to automate labour-intensive tasks and deliver new data insights. However, South African universities face distinctive constraints, including uneven IT infrastructure, limited AI expertise, and cultural resistance to change. These factors influence what can realistically be achieved with AI and highlight why context is important. Understanding this environment allows us to assess whether GenAI's potential can be realised and to identify the adaptations required for success.

7.3 What was already known and what was not

Earlier studies have shown that AI and other digital tools can simplify administrative processes and enhance decision-making within universities. For example, global studies note AI's ability to automate paperwork, improve budgeting, and personalise student support (Williams, 2025). Some experts already argued that higher-education administration is "ripe for GenAI" automation (Williams, 2025). However, limited research has focused specifically on GenAI's role in addressing the financial challenges of South African universities. Prior to this study, both practitioners and scholars recognised AI's potential but lacked clarity on how it could respond to South Africa's unique issues, such as reduced state funding and rising student debt.

This research contributes new insights by presenting empirical evidence from South African institutions. It reflects the perspectives of senior leaders across diverse public universities and identifies practical AI use cases. For example, it shows how local institutions are already exploring AI-driven short courses, automated financial tools, and student analytics, thereby filling a gap in existing literature. The findings also underline the distinct relevance of certain strategies in the South African context; such as using GenAI to manage constrained state subsidies, address high student debt, and develop culturally relevant applications like local-language AI tools. In short, we now know more specifically

what GenAI solutions university leaders find realistic and valuable. The study offers a framework of how GenAI can fit into strategic financial planning, an original contribution that blends cost-cutting and income-generation perspectives.

7.4 Which questions were answered

The research answered the two sub questions clearly. For RQ1 (*how can GenAI be used to reduce operational costs and improve efficiency in South African universities?*), the findings show that university leaders view GenAI as a means to “do more with less” (Kumar et al., 2024). They identified three key mechanisms: automating routine administrative tasks, using analytics to detect inefficiencies and waste, and applying AI-driven forecasting to support more efficient budgeting. For RQ2 (*How can GenAI be used to enhance revenue generation for South African universities?*) the research identified three main avenues: diversifying income through AI-enabled products and short courses, optimising existing revenue by improving student recruitment and success, and enhancing fundraising through donor analytics and grant-matching. By articulating specific use cases and conditions, the research answered the primary question of how AI can improve financial sustainability.

By addressing RQ1 and RQ2, the study collectively answers the primary research question: GenAI can be leveraged to improve financial sustainability in South Africa’s universities by both lowering operating costs and creating new revenue opportunities, provided that institutions develop the necessary capacity and strategies to implement these AI solutions effectively. Fundamentally, GenAI is not a standalone solution, but it can serve as a powerful enabler of financial improvement when applied within a structured and well-defined planning framework.

7.5 How the questions were answered

The study adopted a qualitative, exploratory design. Nine semi-structured interviews were conducted with senior leaders from public universities, including CFOs, CIOs, and other key decision-makers. This purposive sampling approach ensured that participants possessed in-depth knowledge of both university finances and technology. Interview questions probed how GenAI might reduce costs, increase revenue, and what challenges or enablers exist. Data were analysed thematically: the researcher coded the transcripts, grouped similar ideas, and refined themes through iterative comparison. This approach allowed nuanced, context-rich insights rather than broad generalisations. While the sample is small, it provided depth and diversity, with participants from different types of

institutions. The method emphasises understanding perceptions and intentions, acknowledging that large-scale implementations are still rare. Consequently, the findings reflect expert expectations and early experiences rather than quantitative outcomes.

7.6 What was found and how it was interpreted

Cost-related findings: Participants emphasised automation as the most immediate benefit. AI chatbots and scripts can handle routine finance tasks (such as invoice processing, report generation, timetable creation and answering basic queries), thereby cutting labour and outsourcing expenses. Leaders noted that AI could process thousands of student forms in an hour; tasks that previously took days of staff time. Analytics tools can analyse institutional data to uncover inefficiencies and unnecessary spending, such as overspending on catering or the underuse of facilities. AI-driven forecasting can also accelerate budgeting processes and identify financial variances earlier. Collectively, these applications help contain costs without compromising service quality. However, participants cautioned that success depends on several enabling factors, particularly data quality, IT infrastructure, and skilled personnel. Without reliable data and well-integrated systems, AI cannot generate accurate insights. Moreover, implementation efforts must consider staff roles and proactively address fears of job displacement. Thus, automation is a powerful enabler but not a silver bullet.

Revenue-related findings: Leaders saw GenAI as a catalyst for new revenue. They were excited about using AI to create marketable products and services; for example, AI-driven chatbots that other institutions or companies might license, or virtual laboratory simulations that schools could use. They also intended to introduce short courses and micro-credentials in AI and data science, targeting working professionals as well as international learners. AI could improve student recruitment by predicting which applicants are more likely to enrol and succeed, enabling targeted outreach. Early-warning systems could flag at-risk students so that universities can intervene and retain them, thus protecting tuition income. Dynamic pricing models could set fees for executive programmes based on demand, maximising margins. AI analytics can also enhance fundraising and grant acquisition by identifying potential donors and linking researchers with relevant funding opportunities. These approaches demonstrate that AI is not only a tool for cost reduction but also a driver of innovation and competitiveness in emerging markets. However, participants emphasised that achieving revenue growth requires thoughtful planning. AI-generated content must adhere to academic quality standards,

marketing initiatives still need human oversight, and ethical considerations (particularly around data privacy) must be carefully managed.

Interpretation: The findings reflect a sense of cautious optimism. GenAI offers credible ways to reduce costs and generate revenue, but only if universities invest in the right foundations. Respondents said AI should augment, not replace, human expertise. They valued AI for freeing staff from heavy workload and enabling them to focus on strategic or academic tasks, but they also emphasised that human intervention remains essential. The study therefore supports the view that AI can enable South African universities to adapt global technological advances to local priorities. It demonstrates that successful AI adoption depends on a dual commitment; strengthening technological readiness (through reliable data, integrated systems, and effective algorithms) and investing in people (including their skills, culture, and ethical awareness). This perspective highlights that GenAI's true value lies in the balance between technological capability and human judgment. This is a crucial contribution because it shifts the conversation from "Can AI save struggling universities?" to "How exactly can AI help, and what do we need to do to harness it?", a far more actionable discourse for decision-makers.

7.7 How the research contributes to scholarly debate

This study's conclusions must be viewed in light of prior literature, as discussed in Chapter 2, to appreciate what was already known and what new insights have been added. Before this study, the literature had already shown that AI (and GenAI in particular) holds potential for improving efficiency in higher education administration and for driving innovation in educational services. Global research had demonstrated AI's capacity to automate processes and support strategic decision-making for cost reduction, while earlier studies speculated on its ability to enhance student engagement and generate new revenue streams. However, much of this evidence remained theoretical or was derived from contexts not directly comparable to the financial challenges faced by South African universities. There was a notable gap regarding empirical evidence in the context of systemic financial stress, especially for South African or African institutions. The literature also documented the challenges in African higher education (limited AI uptake due to infrastructure deficits, policy and regulatory hurdles, and skills shortages) suggesting that the environment in which any AI solution must operate is uniquely constrained.

This research contributes to the literature by filling that contextual and empirical gap. It examines GenAI specifically as a tool for promoting financial sustainability within South

Africa's higher education sector, grounding the analysis in practical insights from university leaders. In doing so, the study broadens the academic conversation in several important ways. First, it provides evidence that complements and validates international literature in a local context. For instance, where scholars like Han et al. (2024) or Kumar et al. (2024) submitted GenAI could address inefficiencies, this study's participants confirmed that automation of administrative tasks is indeed seen as a viable efficiency tactic in South African universities. The alignment between the study's findings and global theory lends confidence to the idea that AI's benefits are not confined to well-resourced environments; they are recognised even in resource-constrained settings, reinforcing the universal value of AI for organisational efficiency. Second, the study adds new knowledge about priorities and feasibility. The interviews revealed which GenAI applications stakeholders find most attractive or most feasible in practice. For example, the strong interest in AI for student recruitment and new online programmes indicates that South African universities might lean more towards revenue innovation when pressed financially, perhaps even more so than some developed-country institutions that have larger endowments or state support. This emphasis on revenue diversification (alongside cost cutting) contributes to literature by highlighting the dual approach needed in severe funding crises; universities must pursue both sides of the sustainability equation. Prior research hadn't empirically illustrated this dual strategy in the AI, and South African universities, context; this thesis provides that perspective. Third, the study contributes a conceptual framework (developed in Chapter 6) that maps GenAI applications to cost and revenue outcomes within the higher education setting. This framework, derived from empirical evidence, provides a structured lens through which to understand GenAI's integration into university financial management. It represents a theoretical contribution that future researchers can test, adapt, or extend in different contexts. In essence, it connects technology adoption theory with higher education management by introducing a model tailored to the application of AI in university finance. Furthermore, the study contributes to the wider discourse on the 4IR in education (as highlighted by the Council on Higher Education, 2024) by offering a practical case of how 4IR technologies can be applied to address urgent challenges in educational management. This enriches the academic and policy conversations by moving beyond abstract potentials and demonstrating what is happening (and what could happen next) on the ground.

In reflecting on the research context and its importance, it is clear that this study was situated at the intersection of a national higher education funding crisis and a technological revolution. The context of South African universities (grappling with financial strain amid

student protests over tuition fees, declining government subsidies, and post-pandemic recovery) renders the exploration of GenAI not only academically significant but also urgently relevant. The findings underscore that the context influenced the results; for example, unlike studies in wealthier contexts that might focus purely on efficiency gains, South African participants spoke equally about survival, social responsibilities, and the need to expand access (e.g. reaching the “missing middle” students through cheaper online offerings). Thus, this research added to the literature an important contextual nuance; in developing or crisis contexts, technological solutions like AI are viewed through a dual lens of efficiency and access/equity. University leaders are trying to balance financial sustainability with their educational mission under very constrained conditions. The contribution of this research lies in bringing the voices and experiences of university leaders into the academic dialogue. It reinforces the idea that any technological intervention in education should be assessed not only for its economic value but also for how well it aligns with institutional values and constraints.

In conclusion, the research advances knowledge by validating theoretical propositions, presenting new empirical evidence, and offering a contextually grounded understanding of GenAI’s role in higher education finance. It has laid an academic foundation that others can build upon and has supplied practitioners (university executives and policymakers) with research-backed evidence to inform their strategies. The following sections translate these insights into practical recommendations and suggest how future research can further expand on the findings of this study.

7.8 Practical recommendations for stakeholders

Building on the study’s findings, this section presents targeted recommendations for key stakeholder groups within South Africa’s higher education sector. The objective is to guide university management, government policymakers, and academic staff on practical actions that can help achieve the identified cost and efficiency improvements while addressing the challenges highlighted earlier. These recommendations flow directly from the evidence gathered; they are practical steps suggested by the patterns in the data and aligned with the successful approaches implied by participants.

For University Management and Leadership

University executives and management (such as Vice-Chancellors, CFOs, CIOs) are the primary decision-makers responsible for driving GenAI initiatives. Drawing from the study’s findings, the following actions are recommended for this group:

- *Develop a Strategic AI Roadmap:* University management should establish a clear GenAI integration strategy aligned with institutional objectives. This involves identifying priority areas where AI can reduce costs (such as administrative processes and facilities management) and where it can create new revenue streams, including marketing and online programmes. A phased roadmap ensures that AI initiatives are coordinated rather than ad hoc, collectively contributing to financial sustainability. The strategy should incorporate pilot projects with defined goals (for example, a chatbot for student queries aimed at reducing call centre costs) and measurable success indicators such as cost savings, response times, and user satisfaction. These pilots can be reviewed and scaled up if proven effective. Management should also benchmark against early adopters, starting with small, achievable AI applications to build confidence and demonstrate proof of concept before expanding to more complex implementations.
- *Invest in Infrastructure and Skills:* The research emphasised that without adequate digital infrastructure and skilled personnel, AI initiatives are unlikely to succeed. University leaders should therefore prioritise investment in the necessary technological foundations (such as hardware, software, and data systems) while simultaneously building staff capacity through training and development programmes. This could involve upgrading data management systems to ensure clean, comprehensive datasets for AI tools to analyse, and investing in cloud services or computing power for AI workloads. Simultaneously, management should provide training programs or hire specialists so that there are knowledgeable personnel (data scientists, AI developers, or technically skilled staff) to implement and maintain GenAI solutions. Partnerships with technology firms or startups can be explored to supplement internal expertise, particularly where in-house skills are limited. By strengthening both the technical infrastructure and staff capabilities, university management can create an enabling environment for AI to achieve its intended impact.
- *Advance an Innovative and Inclusive Culture:* Change management is essential for the successful adoption of GenAI. University leaders should foster a culture of innovation where staff across all levels are encouraged to suggest and pilot AI-driven improvements within their workflows. This can be achieved by sharing success stories, recognising and rewarding teams that deliver measurable efficiency gains, and establishing cross-departmental innovation committees. Equally important is ensuring that this culture remains inclusive. Management should actively involve both academic

and administrative staff in the AI adoption process to encourage buy-in and reduce anxiety. Transparent communication is key; staff should understand that GenAI tools are intended to support them by removing repetitive work and enabling more meaningful tasks, rather than replacing their roles arbitrarily. Engaging employees through workshops and feedback sessions during implementation can help surface concerns (such as those related to job security or ethics) and foster trust. Leaders should also establish clear ethical guidelines for AI use, aligned with institutional values and South African data protection regulations, to ensure responsible and transparent implementation.

- *Align AI Initiatives with Financial Goals:* Finally, university management should ensure that every GenAI initiative is linked to clear financial sustainability objectives. For cost-related projects, this means setting measurable targets for savings or efficiency improvements, such as reducing processing times by 50% or achieving specific operational cost reductions. For revenue-related initiatives, goals could include increasing enrolment, generating new income through online courses, or improving fundraising performance. By consistently tracking these metrics, management can evaluate the return on investment of GenAI projects. Where outcomes fall short, leadership can make timely adjustments or discontinue ineffective approaches. This disciplined, results-driven implementation approach ensures that financial benefits are realised rather than lost in technological enthusiasm. It also strengthens the business case for GenAI adoption, providing credible evidence that can be shared with councils, funders, and other stakeholders to support continued investment in successful initiatives.

For Government and Policymakers

Government entities (particularly the Department of Higher Education and Training (DHET), the National Treasury, and related agencies) have a pivotal role in establishing an enabling environment for the adoption of GenAI within universities. Based on the study's context and findings, the following recommendations are proposed for policymakers:

- *Provide Funding and Incentives for AI Adoption:* The government should establish dedicated funding streams or grants to assist universities in piloting and scaling GenAI projects focused on cost reduction and operational efficiency. Given the financial constraints faced by many institutions, targeted funding (such as innovation grants or

a dedicated AI modernisation fund) could provide the initial investment needed to launch initiatives that universities might otherwise be unable to pursue. Additionally, incentive mechanisms could be put in place; for example, matching funds or performance-based subsidies for universities that achieve demonstrable savings or income generation through AI. This aligns public investment with the goal of financial sustainability; the short-term injection of funds enables long-term self-sufficiency improvements. Policymakers should recognise that enabling universities to invest in digital infrastructure and AI tools now can reduce the need for bailouts or emergency funding later by improving the institutions' financial health.

- *Develop National Guidelines and Support Networks:* To promote consistent and effective use of AI across the higher education sector, the government (potentially through the Council on Higher Education (CHE) or other relevant bodies) should develop national guidelines or a framework for AI in higher education administration. Such a framework would provide universities with a clear reference for best practices, ethical standards, data privacy, and security protocols when implementing GenAI. It would also help address common concerns, such as protecting student information within AI systems, and establish baseline requirements to ensure quality and maintain public trust. In addition, policymakers should consider facilitating a national network or consortium to enable collaboration and knowledge-sharing among universities. Many participants in this study noted that institutions are currently experimenting with AI in isolation. A government-supported consortium could allow universities to exchange lessons learned, share tools and resources, and even collaborate on joint AI initiatives (such as a shared AI service for smaller institutions). This collective approach would reduce duplication of effort and ensure that even resource-limited universities benefit from sector-wide innovation.
- *Strengthen Digital Infrastructure Nationwide:* The state also carries a broader responsibility to strengthen the ICT infrastructure on which universities depend. Many of the efficiency challenges in South Africa's higher education sector stem from outdated systems and limited connectivity. Government efforts to expand broadband access, upgrade campus networks, and invest in national research and education infrastructure would directly enhance the sector's readiness for AI adoption. Policymakers should thus integrate the needs of "smart universities" into national digital strategy; ensuring that universities, as critical knowledge institutions, are prioritised in infrastructure upgrades (e.g. through subsidised high-speed internet or

cloud computing capacity for public universities). By narrowing the digital divide and strengthening baseline technological capacity, the government can ensure that all universities (not only the well-resourced ones) are able to adopt GenAI tools as practical and sustainable options.

- *Policy and Regulatory Support:* Policymakers should also work to resolve regulatory uncertainties that may hinder AI adoption. Establishing clear policies on data governance in education (defining who owns and can use educational data for AI applications) along with ethical guidelines for AI use in public institutions, would promote greater confidence and accountability. In addition, incorporating AI readiness into institutional audits and oversight processes could further encourage responsible and consistent adoption across the sector. For example, incorporating a review of how institutions are innovating for efficiency into the oversight process could motivate universities to pursue GenAI projects and report on them. Furthermore, the government can support human capacity development by funding AI and data science training programs targeted at the higher education sector's workforce. In summary, a holistic policy approach (combining funding, guidance, infrastructure, and regulation) is recommended to help universities leverage GenAI in a way that strengthens the public higher education system's sustainability and performance.

For Academic and Administrative Staff

Academic staff (lecturers, professors, and researchers) and administrative personnel (managers, officers, and support staff) are the individuals who interact most directly with GenAI tools in their daily work. Their acceptance and effective use of these technologies are critical to success, as reflected in the study's findings on organisational culture and change management:

- *Engage with AI Initiatives and Provide Input:* Staff should take an active role in engaging with their institution's AI initiatives. Instead of viewing GenAI as a top-down directive, employees can contribute by participating in pilot projects or committees responsible for designing and testing AI solutions. For example, administrative teams in finance departments could assist in training an AI tool for invoice processing by sharing their operational expertise, ensuring that the solution reflects real workflow needs. Similarly, academic staff could volunteer to test AI systems designed to assist with grading or student feedback and provide constructive input to improve usability and accuracy. Through participation, staff not only help shape tools that are more

practical and user-friendly but also develop a sense of ownership over technological innovation. The study revealed that many effective AI ideas originate from frontline experiences. Staff are therefore encouraged to identify repetitive administrative tasks or unmet student needs that could benefit from AI intervention. Active engagement at this level ensures that GenAI tools are aligned with the actual needs, context, and workflows of the university environment.

- *Pursue Upskilling and Embrace Lifelong Learning:* To work alongside AI, staff may need new skills. It is recommended that both academic and administrative personnel take advantage of (or request) training opportunities related to digital skills and AI literacy. Universities and perhaps unions or professional bodies should facilitate workshops on understanding GenAI, data interpretation, and using specific AI-driven software relevant to one's role. For instance, academic staff could learn to use AI tutoring systems to enhance their teaching, while administrative staff might be trained to operate new AI-powered student information systems. Through upskilling, staff can overcome uncertainty and become more confident in integrating AI into their daily tasks, thereby improving productivity rather than perceiving the technology as a threat. A mindset of lifelong learning and adaptability is essential. As one interviewee observed, universities that prosper will be those whose staff are willing to evolve their practices alongside technological change. Moreover, staff who develop AI-related competencies may unlock new career opportunities, including emerging roles such as departmental "AI champions" or data analysts supporting digital transformation efforts.
- *Collaborate to Redefine Roles and Processes:* The introduction of GenAI will inevitably reshape certain roles and processes within universities. Staff are encouraged to work collaboratively with management to rethink workflows so that AI assistance is used most effectively. Instead of continuing with traditional methods and merely adding an AI tool on top, processes can be redesigned to take full advantage of automation. For example, if an AI system manages first-level student queries, administrative staff could focus on more complex or personalised student support. Similarly, academic staff might use AI for routine grading in large classes, allowing them to dedicate more time to mentoring or research. These adjustments should be discussed within teams to determine how the time saved through AI can be redirected to activities that add greater value. By viewing AI as a tool that complements rather than replaces human work, staff and managers can collaboratively redefine job roles to emphasise tasks that AI cannot perform (such as creative problem-solving, interpersonal engagement,

and strategic planning). This proactive approach helps to reduce anxiety and fosters a shared sense of purpose, allowing staff to envision a sustainable and meaningful role within an AI-enabled university.

- *Maintain Ethical and Quality Standards:* Lastly, staff share the responsibility of upholding the university's ethical and quality standards when using GenAI. This requires vigilance in areas such as data privacy (ensuring that sensitive student or financial information is not exposed to unsecured AI tools) academic integrity, by avoiding uses of AI that could undermine learning or fairness, and quality assurance, by verifying the accuracy of AI-generated outputs. For example, when an AI system produces a draft report or analysis, staff should critically review and refine the content, applying their professional judgment. Academic staff should also ensure that any AI-generated course materials meet pedagogical standards and are free from bias or factual errors. By serving as an ethical and quality checkpoint, staff help ensure that AI remains a tool that supports, rather than detracts from, the university's mission. The study's participants were optimistic but also cautious; they stressed that human oversight is crucial. Therefore, staff should embrace AI with both openness and critical thinking, ensuring that the core values of education (such as equity, accuracy, and intellectual rigor) continue to guide all practices. When staff model responsible AI usage, they also set a positive example for students and the broader community about how to integrate technology in a principled way.

These stakeholder-specific recommendations provide a roadmap for moving from insight to action. If university leaders champion strategic AI use, government facilitates and supports the necessary environment, and staff engage constructively with the changes, the South African higher education sector can progressively unlock GenAI's benefits. Ultimately, the goal of these recommendations is to ground the study's findings in real-world steps that can help universities become more financially resilient and efficient while still fulfilling their academic and social mandates.

7.9 Limitations of the study and future research

As with any research, this study has limitations that must be acknowledged, and it opens avenues for future inquiry. First, our research design was qualitative and exploratory, involving a relatively small sample of nine interviews from senior stakeholders at South African universities. While this provided rich insights into perceptions and strategic thinking, the findings are inherently context-specific and based on subjective viewpoints.

The sample may not capture the full diversity of perspectives across all universities, especially beyond the ones represented. Thus, one limitation is generalisability; the extent to which these findings apply to other institutions (for example, smaller universities, private universities, or those in other countries) is not certain. Future research could expand on this study by examining a wider range of institutions (through surveys or a larger set of interviews) to determine whether similar themes emerge or whether different contexts highlight new priorities for AI adoption.

Secondly, the study's focus on senior leaders' perspectives provides primarily an executive-level, strategic view of GenAI adoption. It did not include the direct perspectives of other stakeholder groups such as academic staff (who may be responsible for implementing AI within their departments), frontline administrative employees (who engage with AI tools in their daily work), or students (who experience the outcomes of AI-driven initiatives such as chatbots or early-warning systems). These groups may hold different perceptions or concerns about AI; for example, academic staff might raise questions about academic integrity, while administrative personnel could express anxiety about job security. Future research should include these additional voices to offer a more comprehensive view of the institutional change process associated with AI adoption. A multi-stakeholder case study within a single university, examining an AI implementation from several perspectives, could complement the top-down insights provided in this study.

Another limitation is that the research was conducted at a specific point in time (during 2025) when the use of GenAI in university administration was still emerging and evolving. The technology (such as large language models, predictive analytics tools, etc.) is evolving rapidly. It's possible that within a short span, new capabilities or best practices will emerge that were not known at the time of our interviews. Therefore, our findings represent a snapshot of a quickly moving target. Longitudinal research would be valuable; for instance, following up in a few years to see how the same institutions have progressed, or whether the anticipated benefits and challenges of GenAI materialised as expected. Tracking the outcomes of the pilot projects and initiatives mentioned by our participants would be especially useful to validate whether the predicted cost savings or revenue gains were achieved.

From a methodological standpoint, another limitation is potential response bias. Since our interviewees were mostly champions or at least interested in AI (given they spoke at length about GenAI's potential), there might be an optimistic bias in the data. Critics or those who are sceptical of AI may be underrepresented. While we did hear some cautious notes

regarding challenges, the overall tone was hopeful. Future studies could deliberately include sceptical perspectives or examine institutions that have chosen not to adopt AI, in order to understand counterarguments or reasons for caution. This would help build a more balanced picture and may reveal additional risks or constraints that were not fully explored in the present study.

Looking ahead, several research directions appear promising. One key area is quantitative impact analysis. As more universities adopt GenAI solutions, researchers could gather data on key performance indicators (KPIs); for example, the extent of cost savings following process automation or increases in fundraising after implementing AI analytics tools. Statistical analysis of such data could quantify the real impact of AI interventions on financial outcomes. These studies would complement the current research by shifting the focus from perceived potential to measurable results, thereby providing stronger evidence for (or against) the business case for GenAI in higher education.

Another valuable direction for future research is international comparison. The challenge of financial sustainability in universities is global, and many higher education systems (particularly in the post-COVID era) continue to experience severe budget pressures. Comparative studies could explore how universities in different countries are applying AI in financial management, identifying both shared patterns and distinctive strategies.

For example, institutions in more developed contexts may place less emphasis on basic process automation (as those systems are already efficient) and focus instead on advanced analytics or predictive modelling. Policy environments could also shape adoption trajectories: data protection laws in the European Union or federal funding structures in the United States, for instance, may influence how universities approach AI governance and investment. While South Africa has its own contextual drivers (such as its funding model and recent student protests around fees) it also faces common challenges found elsewhere. Cross-country comparisons could therefore contribute to developing a broader theory of AI in university management.

The study's findings also suggest a conceptual framework where GenAI contributes to cost optimisation and revenue enhancement, moderated by institutional readiness factors. Future research could formalise this into a theoretical model and empirically test it. For instance, scholars might hypothesise that the financial impact of AI is mediated by data quality, staff training, or leadership support, and then validate this through multi-case

studies or survey-based analysis. Advancing this work from exploratory to explanatory and predictive research would strengthen theory-building at the intersection of technology management and higher education studies.

In conclusion, this exploratory research provides an important foundation for understanding GenAI's role in South African higher education. It has mapped key themes and relationships, yet much remains to be explored. Continued research in this area will not only deepen academic understanding but also offer practical insights to help institutions navigate the promising, yet complex, journey of integrating GenAI into their operations.

7.10 Concluding remarks

This research explored the intersection between cutting-edge technology and a critical financial challenge in South African higher education. It demonstrated that, when implemented thoughtfully and strategically, GenAI can form part of the solution to universities' cost pressures and revenue demands. The research addressed its core questions by identifying practical ways in which AI can reduce expenditure and enhance income, while also emphasising the conditions necessary for success.

The research reaffirmed the importance of this inquiry: what is at stake is the long-term sustainability of institutions that are vital to South Africa's social and economic development. Its findings contribute both to academic understanding and to practical decision-making, while reminding us that technology alone is not a cure-all; human vision, capacity, and ethical stewardship ultimately determine success.

By integrating insights from literature and empirical evidence into actionable recommendations, this research aims to empower university and government leaders to make informed, confident decisions about how best to leverage AI. If these recommendations are embraced, South African universities could begin to innovate their way out of financial constraints; using GenAI not merely as a buzzword, but as a practical tool for achieving more with less and generating new value across the higher education sector.

In an era of rapid transformation, the capacity to adapt and adopt such innovations will distinguish institutions that simply endure from those that truly thrive. This study concludes with optimism that, through informed strategy and collaboration, AI-driven advancements can help South African higher education not only overcome current financial challenges

but emerge stronger, more efficient, and better equipped to serve students, staff, and society at large.

Beyond its academic value, this research offers a practical contribution through the conceptual model developed from the findings. The model provides a structured way for university leaders and policymakers to assess where and how generative AI can strengthen financial sustainability. It can be adapted as a planning and decision-support tool for aligning AI investments with cost-saving and revenue-generation priorities. By linking organisational readiness, technology adoption, and financial outcomes, the model translates complex insights into an actionable framework that can inform institutional strategies, policy discussions, and funding decisions. In this way, the research moves beyond theoretical understanding to support real-world application within South African higher education.

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APPENDICES

Appendix A: Interview Guide (60-Minute Semi-Structured Interviews)

1. Participant Background

- Please describe your current role and main responsibilities at your university. (Probe: Do you oversee finance, budgeting, strategy, or operations?)
- How long have you worked in this role or in higher education? (Probe: previous jobs, experience with university planning or administration.)
- What has been your involvement in decisions about budgets, resource allocation, or new technologies at the university?

2. Current Financial Challenges

- Universities often face budget pressures. What are the main financial challenges your university is currently experiencing? (Probe: funding shortfalls, rising costs, limited revenue sources.)
- How have changes in government funding or student aid (for example, subsidies or NSFAS support) affected your planning? (Probe: delays in payments, coverage gaps for “missing middle” students.)
- What difficult trade-offs or cuts has your university had to make recently because of financial constraints? (Probe: on staffing levels, research projects, infrastructure or service reductions.)

3. Awareness and Use of GenAI

- What do you understand by “generative AI” (for example, tools like ChatGPT)? Has the rise of GenAI, which has disrupted higher education practices, reached your institution? Can you give examples?
- Have you or your colleagues used any AI-based tools (such as chatbots, language models, or data analytics) in your work here? If so, in what areas (for example, admissions, finance, or teaching)?
- How would you describe the current level of AI awareness or expertise among staff at your university? (Probe: any training received, informal experiments, or champions of AI.)

4. GenAI for Cost Reduction

- In what practical ways could generative AI help reduce costs or improve efficiency at your university? (For example, by automating routine tasks or optimising resource use.) (Probe: Are there specific processes, such as admissions processing, scheduling classes, maintenance planning or report generation, where AI might save time or money?)
- Can you think of any administrative or academic support tasks that GenAI could automate to lower staff workload? (Probe: answering common student queries, data entry, or summarising reports.)
- What benefits do you see from using AI to analyse university data or workflows? (Probe: predictive analytics to plan budgets or maintenance schedules; detecting inefficiencies.)

5. GenAI for Revenue Generation

- How might generative AI be used to help your university increase revenue? (Probe: attracting more students, developing new online programs, improving research grant success, or forming industry partnerships.)
- Are there new services or products (for example, AI-driven courses, consulting services, or data analysis offerings) that the university could offer to generate income?
- Could AI tools help improve student recruitment, retention or alumni engagement in ways that bring in more funds? (Probe: personalised marketing to prospective students, early warning systems to reduce dropouts, targeted appeals to donors.)

6. Examples of Success or Failure

- Can you share any examples where AI or other technology initiatives have succeeded or failed in helping your university's operations or finances? (Probe: outcomes of past projects, even if not AI-specific.)
- What lessons were learned from those experiences? (Probe: reasons for success or failure, stakeholder buy-in, resource issues.)
- For instance, some studies mention using AI-driven analytics for better resource planning. Have you seen any similar approaches (successful or not) here or in other institutions/organisations?

7. Enablers and Barriers

- What factors would help or hinder using GenAI at your university? For example, do you have the technical infrastructure, data and trained people needed, or are there gaps and constraints (such as outdated IT systems or limited budgets)? (Probe: Consider if leadership support, funding for AI projects, or clear strategy is in place.)
- What is the level of digital and AI skills among your staff? Are there training or expertise gaps that might make adopting GenAI difficult?
- Are there any existing policies, regulations or governance issues (like data privacy rules) that could affect using GenAI? (Probe: concerns about data security, copyright, or need for new guidelines.)
- What resources or support (training, funding, partnerships) would enable more effective AI adoption here?

8. Ethical and Policy Considerations

- What ethical concerns do you have about using generative AI in university operations (for example, data privacy, algorithmic bias, or accountability)? (Probe: Consider concerns about academic integrity, decision transparency, or reliance on AI.)
- How should decisions or advice coming from AI systems be reviewed or governed? (Probe: checks by human experts, clear procedures, audit trails.)
- What kind of policies or principles would you want in place for using GenAI here? (Probe: policies on fairness, human oversight, compliance with laws like data protection.)
- How would you balance innovation with caution when adopting AI solutions in education and finance?

9. Closing Reflection

- Overall, how optimistic or concerned are you about using generative AI to support your university's financial sustainability? Why?
- If you could recommend one action or strategy to university leaders regarding AI and finances, what would it be?
- Is there anything else you would like to add about GenAI, cost management, or revenue strategies that we haven't covered?

Interview Guide References: Questions are informed by recent literature on AI in higher education and finance (e.g. topics of AI-driven efficiency, barriers to adoption, and concerns about AI use):

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Appendix B: Consistency Matrix

RESEARCH QUESTION / OBJECTIVE	KEY LITERATURE SUPPORT	DATA COLLECTION (INTERVIEW GUIDE TOPICS & SPECIFIC PROMPTS)	ANALYSIS PLAN (EXPECTED THEME AREAS & CHAPTER LINKS)
RQ1: How can GenAI be used to reduce operational costs and improve efficiency in South African universities? (RO1: Cost management)	Cost-reduction mechanisms & operations: AI/GenAI streamlines admin workflows, lowers error rates, enables data-driven budgeting/forecasting, RPA, invoice-matching, scheduling, predictive maintenance; industry analyses reinforce labour-time savings and outsourcer substitution (Han et al., 2024; Kumar et al., 2024; HolonIQ, 2023; Verge AI, 2025). Ethical trade-offs & hidden costs flagged in 2.7 (Francis et al., 2025). African constraints (infra, skills, bandwidth)	1. Background (role, budgeting/tech involvement) to situate cost levers by function. 2. Current financial challenges (funding shortfalls, rising costs, NSFAS timing, recent trade-offs) to anchor baseline cost pressure. 3. Awareness & use of GenAI (definitions; existing tools in finance/admissions; staff AI literacy/training) to locate current maturity. 4. GenAI for cost reduction: (a) concrete process automation (admissions processing, scheduling, maintenance planning, report generation); (b) admin/support automation (FAQs/chatbots, data entry, report summarising); (c) analytics for budgeting/maintenance forecasting;	Theme 1: AI-driven cost savings; labour/time, external services substitution, error reduction (Ch.5); Theme 2: AI-driven operational efficiency; cycle time, backlogs, SLAs, space/timetabling, predictive maintenance (Ch.5). Cross-link to Barriers (skills/infrastructure/funding/strategy gaps) and Risks (ROI risk, privacy, reliability) shaping realised savings (Ch.5; Ch.6).

	shape feasibility (Butcher et al., 2021; Kurien & Soglo, 2024). (d) examples of pilot uses (e.g., chatbots replacing call centres); (e) perceived benefits/limits. 6. Examples of success/failure (outcomes, lessons, stakeholder buy-in, resources). 7. Enablers & barriers (infra/data/skills, budgets, leadership support, strategy). 8. Ethics & policy (privacy, bias, academic integrity; review/oversight; policy principles; innovation vs caution). 9. Closing reflection (overall optimism; one recommended action).	
RQ2: How can GenAI be used to enhance revenue generation/diversification in South African universities? (RO2: Revenue generation)	Revenue mechanisms: Recruitment & retention via personalised outreach, early-warning/at-risk analytics, protect tuition; differentiation & intl outreach (Saúde et al., 2024; Batista et al., 2024; Hannan & Liu, 2023; Farrelly & Baker, 2023).	Context & Awareness (baseline revenue pressure; existing AI usage; staff capability). 5. GenAI for Revenue: (a) attracting students (personalised marketing, intl outreach); (b) retention (early-warning interventions); Theme 3: AI for revenue enhancement; higher yield, better collections, productisation, partnerships (Ch.5); Theme 4–6 (cross-cutting) moderate revenue outcomes: Barriers (skills, infra, funding, lack of strategy) and

	New programs / services; micro-credentials, virtual labs, licensable chatbots & digital products (Saúde; Batista; Farrelly & Baker; Hannan & Liu). Fundraising & partnerships; personalised alumni comms; third-stream augmentation (Farrelly & Baker, 2023). Equity/ethics cautions (fairness/digital divide) apply to pricing and access (Francis et al., 2025).	(c) new products/services (AI-driven courses, consulting/data services); (d) research/grant success; (e) partnerships; (f) alumni fundraising; (g) pricing/collections. 6. Examples (successful/failed revenue tech; lessons). 7–8. Enablers/Barriers & Ethics/Policy as revenue constraints (pricing fairness, inclusion, POPIA compliance, governance).	Risks (equity, integrity, privacy, ROI) vs Enablers (leadership, governance, data readiness, skilling, phased wins, collaboration). Integrate fairness constraints for pricing (Ch.5; Ch.6).
Cross-cutting Objective: Identify enablers, barriers & risks that condition GenAI's financial impact (applies to RQ1 & RQ2)	Barriers: skills/AI literacy, cultural resistance, outdated infra, funding constraints, lack of strategy & governance; POPIA/compliance uncertainties; duplication/fragmentation without policy.	7. Enablers & Barriers (infra/data/skills/contracts/budget; leadership/strategy). 8. Ethics & Policy (privacy, bias, integrity; governance/oversight; policy principles; balance innovation vs caution).	Theme 4: Barriers to adoption; Theme 5: Risks of AI implementation and use; Theme 6: Enablers & prerequisites. Use these to interpret variance in RQ1/RQ2 outcomes and to justify balancing/limiting loops

	Risks: academic integrity/misuse, privacy/security, bias/fairness/digital divide, reliability/oversight, ROI risks. Enablers: leadership vision, strategy & governance, infra/data readiness, skilling/training, phased implementation & quick wins, collaboration/partnerships (incl. student co-creation; sector forums). (Ch.2, 2; Ch.5).	9. Closing (overall stance, top action). Plus 2–3 context & 6 lessons as conditioning evidence.	in the Ch.6 model narrative and recommendations. (Ch.5; Ch.6).
Theoretical alignment (frames mechanisms & conditions; informs coding lenses)	Theoretical foundations: RBV/Dynamic Capabilities (capability reconfiguration for efficiency & new value), DOI (adoption/thresholds), acceptance lenses for perceptions & use; used to explain where/why cost/revenue effects emerge, and what capabilities must be built to unlock loops.	3. Awareness & Use; 7. Enablers/Barriers; 8. Ethics & Policy; for coding theoretical mechanisms (perceived usefulness/ease; resources; governance).	Apply theories during axial/synthesis coding in Ch.6 to explain reinforcing vs balancing loops and capability prerequisites for financial impact (e.g., data readiness, efficiency loop; governance/ethics, constraint loop).

	(Also critique of global literature & need for contextual balance of benefits/risks).		
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