



Artificial Intelligence Adoption and Implementation in Zambia's Public

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This study examined artificial intelligence (AI) adoption and implementation in the public university libraries of the University of Zambia, Copperbelt University, Chalimbana University and Mukuba University. Guided by the Technology–Organisation–Environment framework, UTAUT2, Diffusion of Innovations and Institutional Theory, it adopted a pragmatist paradigm and convergent parallel mixed-methods design. Quantitative data were collected from students, complemented by interviews with 13 key

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1. Introduction

Artificial intelligence (AI) is an increasingly important technological development, with applications

It is also worth noting that the growing application of AI in higher education has created opportunities to enhance teaching and learning, research, administration, student support and information provision. Studies show that AI can facilitate personalised learning, automate routine activities, process large

volumes of data and improve access to information and research support (George and Wooden, 2023; Allam et al., 2025; Alotaibi, 2024). At the same time, its use presents concerns relating to privacy, academic integrity, data protection, algorithmic bias, misinformation, transparency, accountability and changing professional roles. These developments have made the actual use of AI an increasingly important area of inquiry, particularly as higher education institutions seek to integrate emerging technologies into their teaching, research and support services.

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In Zambia, the government has taken steps to promote AI integration across various sectors. The National Artificial Intelligence Strategy, developed in 2024, seeks to create an enabling environment for the responsible adoption and implementation of AI across the economy (Ministry of Technology and Science, 2024). Within this policy context, understanding AI adoption and use in public university libraries has become increasingly important. Such evidence can establish whether AI has progressed from professional and academic discussion to practical library operations and services (Alam et al., 2024; Subaveerapandiyana et al., 2023; Modiba and Chisita, 2023). Accordingly, this study sought to identify the AI technologies in use in the academic libraries of the University of Zambia (UNZA), Copperbelt University (CBU), Chalimbana University (CHAU) and Mukuba University (MKU); examine their applications in library functions and services; and investigate the technological, organisational and environmental factors influencing their use. By focusing on actual AI use, the study provides empirical insights into emerging AI practices in Zambian academic libraries and contributes to scholarship on AI and academic librarianship in developing-country contexts.

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2. Literature Review

a). AI Technologies and Applications in Academic Libraries

AI is increasingly being incorporated into academic library services and operations. Intelligent search and discovery systems can improve information retrieval, while recommendation systems suggest resources aligned with users' needs. Chatbots can support reference and enquiry services by automating responses to routine questions, while machine learning facilitates classification, cataloguing and metadata generation. Robotics and automation also support selected operational functions (Gujral et al., 2019; Lee et al., 2021; Jinendran and Kumar, 2023; Ram, 2023; Meesad and Mingkhwan, 2024). Generative AI has further broadened this landscape through tools such as ChatGPT, Gemini, Copilot and DALL-E, which can support information synthesis, summarisation, content creation, translation, research assistance and user education. Fang et al. (2025) highlight the relevance of these tools to content creation, information services and workflow support in academic libraries. AI applications are therefore extending beyond specialised library systems to general-purpose tools that can be integrated into research and information services. Nevertheless, technological availability and potential applications should be distinguished from evidence of actual use and the factors influencing adoption in practice.

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b). Empirical Evidence on AI Use in Academic Libraries in Developed Countries

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Hervieux (2019) found that U.S. academic libraries were experimenting with chatbots, automated

In Canada studies showed that awareness and interest in AI did not correspond with widespread operational use. A study by Hervieux and Wheatley (2021) found varying levels of AI knowledge among Canadian and U.S. academic librarians and reported strong interest in training and professional development. However, Guy et al. (2023) who examined 106 Canadian academic libraries, found that only two used Chatbots for reference services, while 78 provided conventional live chat. This finding is significant as it illustrates the distinction between recognising the potential of AI and incorporating AI technologies into routine library services. Further, Gupta (2025) study at University of Toronto emphasised on the value of small-scale experimentation in developing institutional experience with AI. China provided evidence of a broader range of applications. Li (2024) reported that 26% of surveyed libraries had implemented AI-driven indexing tools, while 16.9% planned future AI services. Reported applications included search improvement, automation, cataloguing, digitisation, and chatbot-supported responses. Additionally, Huang et al. (2023) identified intelligent question-and-answer systems, smart talking robots, and AI search engines among technologies implemented in Chinese universities. The documented Xiaotu, an AI-enabled talking robot at Tsinghua University Library, which was used to provide virtual reference and participatory services showed the depth of AI implementation in the Chinese library context (Yao et al., 2015). These studies indicate that AI can be integrated into both user-facing and technical library functions, although evidence from leading institutions may not necessarily represent less-resourced universities.

Studies from the United Kingdom similarly identify applications across several areas of academic library practice. Huang et al. (2023) reported applications including automated storage and retrieval systems, enquiry robots, and machine-learning-based resource guides. Cox et al. (2019) identified applications in resource discovery, scholarly communication, data curation, and personalised learning, while Cox (2024) highlighted automated cataloguing, intelligent discovery, recommendation systems, and data management. Taken together, evidence from developed countries demonstrates that AI is already being used in a variety of academic library functions, but the level of implementation remains uneven.

6). AI Use in Academic Libraries in Developing Countries

Evidence from developing countries presents a similar pattern of growing but uneven use. In India, studies have identified intelligent cataloguing, chatbots, recommendation systems, OCR, smart shelving, robotics, plagiarism detection, grammar-checking tools, and generative AI among technologies being used or increasingly introduced in library practice (Malakar et al., 2025; Subaveerapandiyan and Gozali, 2024; D'Souza, 2024). These findings demonstrate that AI applications can extend across technical services, information services, and research support. However, the literature also identifies infrastructure, staff training, institutional alignment, privacy, transparency, and concerns about job displacement as important challenges.

Malaysia provides further evidence that the extent of AI use is associated with institutional capacity. Masrek et al. (2025) reported moderate readiness in infrastructure and management support but weaknesses in funding and policy development. Sapri et al. (2024) identified AI-supported personalised recommendations and content marketing while highlighting concerns relating to digital inequality, privacy, infrastructure, and staff training. Okunlaya et al. (2022) further proposed an AI library services

framework to support digital transformation, while noting the need for empirical validation across different institutional settings.

As part of developing-country contexts, African countries provide a more relevant comparative context for examining AI use in Zambia. Studies from India, South Africa, Nigeria, and Ghana generally indicate

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Studies from Nigeria demonstrate similar constraints. A study by CLN (2023) found limited AI implementation among university libraries in Southern Nigeria, with security scanning systems among the more commonly reported applications, while robotics, chatbots, RFID, facial recognition, and AI-enabled cataloguing were largely absent. Owolabi (2022) reported low readiness for robotic technologies because of inadequate infrastructure, funding, and policy support. Agboke and Oladokun (2024) identified AI robotics, automated cataloguing, and intelligent retrieval as promising applications but highlighted infrastructure, financial, skills, privacy, and job-displacement challenges. Salman et al. (2023) likewise reported limited operational use of AI in Kwara State, while Adejo and Misau (2021) identified expert systems, natural language processing, robotics, and AI-supported reference and technical services as potential areas of application.

In Ghana, the studies indicate somewhat broader use of selected AI applications. Adjei and Agyeman (2024) found that AI-driven search engines and automated cataloguing were among the more implemented technologies, while chatbots and recommender systems were emerging. Danquah et al. (2024) similarly identified search engines, automated cataloguing, and chatbots, while reporting constraints related to funding, infrastructure, training, institutional resistance, and job displacement. Amoah and Minishi-Majanja (2023) found that many Ghanaian university libraries had limited application of Fourth Industrial Revolution technologies despite awareness of their potential.

The literature establishes that AI is no longer solely a prospective technology in academic libraries, with applications including intelligent search systems, automated cataloguing, chatbots, recommendation systems, robotics, optical character recognition (OCR) and generative AI. However, the extent of implementation varies considerably across institutions and contexts, suggesting that evidence from technologically advanced settings cannot automatically be generalised to academic libraries in developing countries. Evidence from Africa similarly indicates that AI adoption in academic libraries is emerging but remains uneven. Existing studies identify infrastructure, funding, staff competencies, institutional support and policy environments as important factors shaping the transition from awareness and experimentation to routine use. These contextual differences highlight the need for empirical research examining the extent of actual AI use and the factors influencing its adoption within specific national and institutional settings.

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g). AI Use in Academic Libraries in Zambia

Evidence concerning AI use in Zambian academic libraries remains limited. Existing studies indicate growing awareness of AI and emerging use of AI-related technologies, but they do not yet provide a comprehensive account of the technologies currently being used across public university libraries.

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Subaveerapandiyana et al. (2023) found that Zambian library and information science professionals recognised the potential benefits of AI but expressed concerns relating to job displacement, weak leadership, limited technology, funding, and training. Alam et al. (2024) similarly reported awareness and confidence in AI applications but identified shortages of specialised skills, technology, organisational readiness, and funding as constraints. These studies provide useful evidence concerning professional perceptions and readiness, but they provide limited evidence on the specific AI technologies currently used in academic libraries.

Evidence of particular AI applications is beginning to emerge. Kuyela (2025) reported the use of AI-enhanced cataloguing and chatbots among respondents in Lusaka Province, although the geographical scope of the study limits its representation of public university libraries nationally. Chaamwe (2024) found high awareness and use of generative AI among students at Copperbelt University, while Kanyemba et al. (2023) reported the use of ChatGPT, Grammarly, and Turnitin among staff and students at David Livingstone College of Education for content generation, academic writing, plagiarism detection, and research support. Although these studies demonstrate the growing presence of AI within Zambian educational environments, they do not provide a comprehensive sector-level account of AI use in public university libraries. In particular, there is limited evidence establishing the range of AI technologies currently in use, the library functions and services in which they are applied, and the conditions influencing their use across Zambia's public universities.

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3. Conceptual Framework

This study is anchored in the TOE framework developed by Tornatzky and Fleischer (1990), which provides the overarching structure for examining AI use in Zambia's public university libraries. The framework explains organisational technology adoption in terms of three contexts: technological, organisational, and environmental. The technological context encompasses factors such as infrastructure, connectivity, system compatibility, and availability of appropriate technologies. The organisational context includes management support, financial resources, staff competencies, training, organisational readiness, and institutional policies. The environmental context considers external influences such as government policies, regulations, professional expectations, and developments within the higher education sector.

TOE provides the study's overarching organisational framework, while UTAUT2, DOI and Institutional Theory explain complementary aspects of AI adoption and implementation. UTAUT2 illuminates individual acceptance by focusing on perceived usefulness, facilitating conditions and behavioural intention (Venkatesh et al., 2012). DOI explains how relative advantage, compatibility, complexity, trialability and observability shape the diffusion of AI innovations (Rogers, 2003). Institutional Theory accounts for the influence of policies, norms, regulations and institutional pressures on organisational responses to AI. Together, these perspectives connect individual behavioural intention, innovation

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characteristics, organisational capacity and the wider institutional environment, providing an integrated basis for analysing actual AI use in Zambia's public university libraries.

4. Methodology

The study adopted a pragmatist research paradigm and a convergent parallel mixed-methods design, collecting quantitative and qualitative data during the same phase and subsequently integrating the findings to provide a comprehensive understanding of AI use in Zambia's public university libraries. The study was conducted at four public universities namely UNZA, CBU, CHAU and MKU. Students constituted the quantitative sample, while the qualitative component involved key informants with knowledge of library management, information technology, institutional decision-making and higher education policy.

The quantitative component employed multistage sampling (Creswell, 2004). The nine public universities were stratified into older and newer institutions according to their establishment periods, after which four universities, two from each stratum, were randomly selected. Students were then selected using stratified proportional random sampling based on institutional enrolment. Yamane's formula, with a 5% margin of error, yielded a target sample of 398 respondents. For the qualitative component, 13 key informants were purposively selected from among chief librarians, information technology personnel, university management representatives and the Higher Education Authority. Interviews continued until thematic saturation was reached.

Data were collected using a structured questionnaire and a semi-structured interview guide informed by the TOE framework, complemented by UTAUT2, DOI and Institutional Theory. Both instruments were tested before the main data collection: the questionnaire was piloted with 10 respondents, while the interview guide was pretested for clarity and relevance. Cronbach's alpha coefficients for the quantitative scales ranged from .707 to .871, indicating acceptable to good internal consistency. Quantitative data were analysed using descriptive statistics, Pearson product-moment correlation, and multivariate regression analysis in SPSS Version 31, while qualitative data were analysed thematically. Item-level analyses were based on valid responses to the respective questions, with non-responses treated as missing values for the relevant analyses. Consequently, the number of valid observations varied across analyses. Ethical safeguards included informed consent, confidentiality, anonymity and voluntary participation.

5. Results and Findings

a). AI Technologies, Awareness and Use in Academic Libraries

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Regarding frequency of use, 168 (54.5%) reported daily use of AI-enabled tools, while 85 (27.6%) reported weekly use. Together, daily and weekly users accounted for 253 respondents (82.1%) who answered the item. Monthly use was reported by 22 (7.1%), rare use by 14 (4.5%), and non-use by 19 (6.2%).

b). Modes of Access and Institutional Provision

The findings revealed differences between independent and institutionally mediated access to AI-enabled tools. Of the 309 respondents considered in the access analysis, 268 (86.7%) reported independently accessing AI assistants and writing coaches through personal or freely available accounts, compared with

10 (3.2%) who accessed them through institutional library platforms. For grammar and style checkers, 111 (35.9%) reported independent access, while nine (2.9%) reported institutional access.

Institutional access was more evident for discovery and article-linking services and electronic resource databases, with 98 (32.0%) reporting institutional access. However, 175 (57.2%) indicated that they did not access or use these resources. Non-access or non-use was also high for bibliographic, citation and reference management tools 219 (70.9%) and AI-based summarisation and literature-mapping applications 232 (75.1%). The interview findings complemented these results. Key informants reported that students increasingly used external AI platforms, particularly ChatGPT, but distinguished such engagement from formal AI services provided by academic libraries. Participants also indicated that some existing library products and services contained embedded AI functionality, suggesting that users may encounter AI-enabled features without necessarily recognising their underlying operation. Documentary analysis examined strategic plans from UNZA, CBU, CHAU and MKU. No explicit provisions relating to artificial intelligence were identified in the documents reviewed.

c). Internal Factors Influencing Behavioural Intention to Adopt AI

The second objective examined organisational and technological factors associated with behavioural intention to adopt AI. Organisational factors comprised facilitating conditions and AI literacy, while technological factors comprised performance expectancy, compatibility and effort expectancy.

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d). External Institutional Factors Shaping AI Adoption

The qualitative findings identified several contextual conditions perceived to influence AI adoption and implementation. These included leadership support, institutional policy and governance, digital infrastructure, funding, AI ethics, staff training and organisational culture.

Leadership support emerged as an important condition, particularly when institutional commitment was translated into practical resources and support. Participants highlighted the importance of policies and governance in clarifying acceptable AI use, responsibilities, accountability and safeguards. Uncertainty regarding these arrangements was perceived as creating challenges for responsible and confident engagement with AI. Digital infrastructure and technical support were also identified as important. Participants associated the feasibility of AI adoption with connectivity, computing capacity and the availability of appropriate technological systems. Funding was similarly identified as necessary for infrastructure, technical support and staff development.

AI ethics and responsible use emerged as additional concerns. Participants identified the importance of guidance on appropriate AI use, while staff training was considered relevant to strengthening competence, confidence and readiness. Institutional culture and the wider organisational environment were also identified as conditions that could enable or constrain AI adoption. These factors were derived from qualitative inquiry and were not included as predictors in the quantitative regression models. They

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therefore represent contextual evidence rather than statistically established predictors of behavioural intention.

e). Behavioural Intention and AI Implementation

Further, the Pearson correlation analysis demonstrated a positive and statistically significant relationship between behavioural intention and AI implementation ($r = .572, p < .001$). Simple linear regression further showed that behavioural intention significantly predicted AI implementation, $F(1, 340) = 164.943, p < .001$. The model explained 32.7% of the variance in AI implementation ($R^2 = .327$; adjusted $R^2 = .325$), with behavioural intention making a significant positive contribution ($\beta = .572, p < .001$).

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Discussion

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a). User-Level AI Adoption and Institutional Maturity

The findings demonstrate that AI engagement among users of the four participating universities is more advanced than its formal integration into academic library services. High awareness and frequent use, particularly of general-purpose applications, indicate that AI is becoming integral to academic information practices. However, lower awareness of specialised research tools suggests that engagement remains concentrated on accessible applications rather than the broader range of AI-supported scholarly activities. These findings align with Subaveerapandiyan et al. (2023) and Chipembele et al. (2025), who reported growing AI awareness and positive perceptions among library and information science professionals in Zambia. Adjei and Agyeman (2024) similarly highlighted AI's potential to improve library operations. This study extends previous research by demonstrating frequent user engagement while distinguishing usage frequency from sophistication and institutional support.

Further, DOI theory explains how users may progress towards regular AI use while institutions remain at assessment, planning or experimentation stages (Rogers, 2003). Diffusion therefore varies across individuals and organisations. The TOE framework further explains how institutional implementation depends on infrastructure, organisational capacity, financial resources and environmental conditions (Tornatzky and Fleischer, 1990), challenges also identified in related studies (Yakubu et al., 2023; Molaudzi and Ngulube, 2025; Cox and Wang, 2025; Ayinde et al., 2026). In complement, documentary analysis revealed no explicit AI provisions in the reviewed strategic plans, indicating limited formal strategic recognition rather than an absence of AI-related activities. Taken as a whole, user-level diffusion may outpace institutional integration. AI maturity should therefore be assessed through awareness, independent use, institutional access, formal service provision, governance and strategic alignment.

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b). Organisational, Human and Technological Factors

The quantitative findings demonstrate that facilitating conditions and AI literacy were significant positive predictors of behavioural intention to adopt AI. Facilitating conditions align with UTAUT/UTAUT2, which emphasise enabling resources and support (Venkatesh et al., 2003, 2012), and TOE, which highlights organisational readiness and technological capacity (Tornatzky and Fleischer, 1990). Previous studies similarly identify infrastructure, funding and institutional readiness as important adoption considerations (Alam et al., 2024; Chaamwe, 2024; Subaveerapandiyan et al., 2023; Shahzad et al., 2025). AI literacy highlights the importance of understanding AI capabilities and limitations, evaluating outputs critically, recognising bias and misinformation, and considering privacy, intellectual property and ethical implications (Alam et al., 2024; Molaudzi and Ngulube, 2025). This finding aligns with Kembau et al.

(2026) and research linking skills and knowledge to library technology adoption (Ocholla and Ocholla, 2020; Subaveerapandiyan et al., 2023; Shahzad et al., 2025).

The technological model demonstrated greater explanatory power than the organisational-factor model. Performance expectancy was the strongest predictor, followed by compatibility and effort expectancy. This suggests that perceived benefits and alignment with existing academic and professional practices are particularly relevant to adoption intentions. Performance expectancy aligns with UTAUT2 (Venkatesh et al., 2012), while compatibility reflects DOI's emphasis on fit with existing needs and practices (Rogers, 2003). In academic libraries, this includes integration with information systems, research workflows and professional responsibilities, consistent with Tomiuk et al. (2024). Although effort expectancy was significant, its contribution was smaller, suggesting that perceived benefits and compatibility were more influential in this model. These findings broadly align with previous technology-adoption research (Andrews et al., 2021; Sapri et al., 2024; Kuyela, 2025). Additionally, as the factors were examined in separate regression models, their explanatory power should be compared cautiously. Thus, AI adoption involves technological perceptions alongside organisational and human enabling conditions.

c). External Institutional Conditions and Implementation

The qualitative findings demonstrate that AI adoption is shaped by institutional conditions, including leadership commitment, funding, infrastructure, policy, governance, staff competence and organisational culture. These findings complement the quantitative results but do not establish independent statistical effects for external factors.

Leadership provides strategic direction and legitimacy, while effective implementation requires practical support and resource allocation (Aman and Zakaria, 2024; Lau et al., 2025; Yakubu et al., 2023). Infrastructure and funding determine whether AI applications can be introduced and sustained. Existing platforms, such as Koha and DSpace, may offer opportunities for incremental AI integration where technically appropriate (Malakar et al., 2025; Molaudzi and Ngulube, 2025; Orubebe, 2025).

Policy, governance and ethics are equally important, as concerns about privacy, data protection, intellectual property, plagiarism, misinformation and accountability can create uncertainty. Institutional Theory explains how regulatory, professional and normative pressures shape organisational responses to emerging technologies (Cox, 2019; Okunlaya et al., 2022; Zondi et al., 2024; Sang, 2025). Clear governance can guide responsible use, while staff training and change management strengthen professional competence and ethical practice (Adejo and Misau, 2021; Nwabusi and Jidere, 2024; Aman and Zakaria, 2024; Lau et al., 2025; Ayinde et al., 2026). These findings help explain why widespread individual engagement does not necessarily translate into institutional implementation. Users may access and intend to adopt AI while libraries develop the resources, governance and capabilities required for formal integration. The qualitative evidence therefore identifies contextual conditions warranting further investigation rather than statistically significant predictors.

d). Behavioural Intention and AI Implementation

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Further, the distinction between individual intention and institutional implementation is especially important in the context of the participating universities. Users may independently employ AI applications without their libraries having formally integrated AI into services, workflows or strategic plans. The relationship between behavioural intention and implementation should therefore be interpreted in light of how implementation was operationalised and measured in this study. Moreover, the regression establishes a significant statistical relationship, not by itself a causal effect.

6. Integrated Theoretical Interpretation

a). An Integrated Framework for AI Adoption and Implementation in Zambia's Public University Libraries

The quantitative findings provide empirical support for the relationships between the examined technological and organisational factors and behavioural intention to adopt AI. Within the technological-factor model, performance expectancy was the strongest predictor of behavioural intention ($\beta = .393$, $p < .001$), followed by compatibility ($\beta = .295$, $p < .001$) and effort expectancy ($\beta = .094$, $p = .037$). The model explained 45.5% of the variance in behavioural intention. The organisational-factor model explained 22.1% of the variance, with facilitating conditions ($\beta = .307$, $p < .001$) and AI literacy ($\beta = .264$, $p < .001$) both making significant positive contributions. These findings indicate that behavioural intention is associated with perceived technological benefits, compatibility, ease of use, enabling resources and AI-related competence.

The relationship between behavioural intention and AI implementation provides a further empirical component of the framework. Behavioural intention significantly and positively predicted AI implementation ($\beta = .572$, $p < .001$), explaining 32.7% of its variance. This finding supports the view that behavioural intention is an important component of the adoption process, consistent with UTAUT and UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012). Nevertheless, the unexplained variance indicates that behavioural intention alone does not account for all variation in implementation.

The framework also draws on DOI to explain how AI engagement may progress from awareness and experimentation towards adoption and implementation (Rogers, 2003). The findings indicate that individual users may become aware of and regularly use AI tools before their institutions formally incorporate such technologies into library services and workflows. This distinction is important because individual adoption does not necessarily constitute organisational adoption, while implementation requires the translation of an adoption decision into operational practice.

TOE provides a complementary explanation of the organisational conditions surrounding this process (Tornatzky and Fleischer, 1990). The qualitative findings identified leadership support, digital infrastructure, funding, staff training, policy and governance, ethical considerations and organisational culture as relevant institutional conditions. These findings suggest that the progression from behavioural intention to institutional implementation occurs within a wider environment that may enable or constrain the integration of AI. However, because these external factors were investigated qualitatively rather than included in the regression models, the framework does not present them as statistically established predictors.

Institutional Theory further informs the framework by explaining how regulatory requirements, professional expectations, governance arrangements and the pursuit of institutional legitimacy may shape organisational responses to AI (Cox, 2019; Okunlaya et al., 2022; Zondi et al., 2024; Sang, 2025). In

academic libraries, these considerations are particularly relevant to responsible AI use, data protection, intellectual property, accountability and professional practice. Institutional policies and governance arrangements may therefore help establish the conditions under which AI can be adopted and integrated responsibly.

Figure 1.0 presents the integrated framework developed from the study findings. It distinguishes the technological and organisational factors quantitatively examined as predictors of behavioural intention from the relationship between behavioural intention and AI implementation. It also incorporates the external institutional conditions identified qualitatively, recognising their contextual relevance without implying that their independent statistical effects have been established.

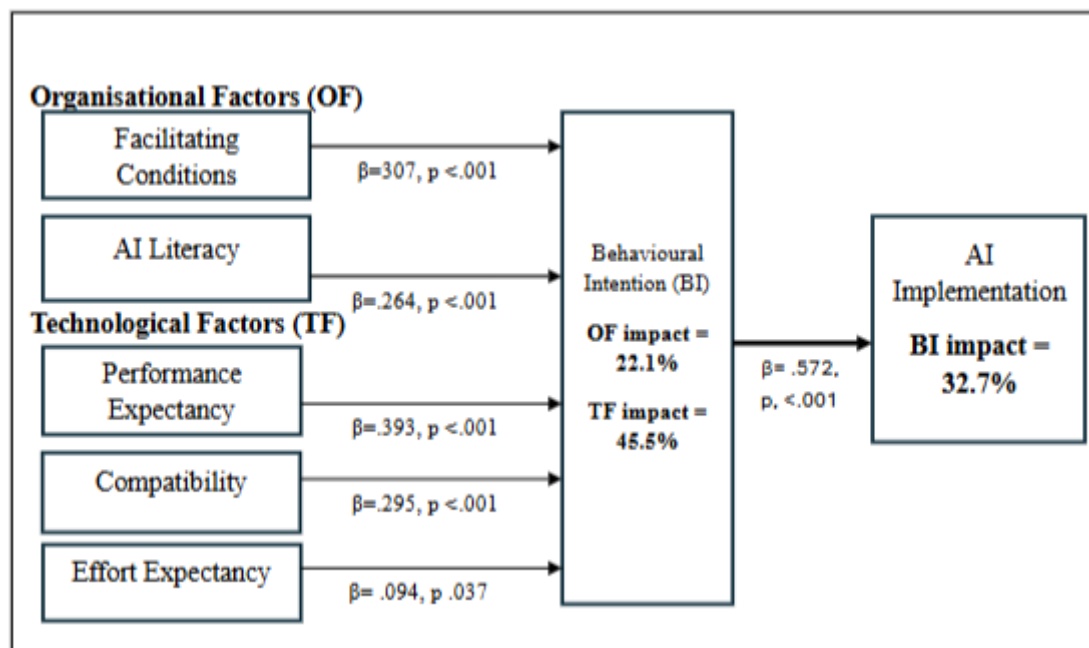


Figure 1.0: Integrated framework for AI adoption and implementation in Zambia's public university libraries.

The framework's principal contribution is its distinction between individual AI engagement, behavioural intention and formal institutional implementation. It illustrates how technological perceptions and organisational and human capabilities are associated with behavioural intention, while the wider institutional environment provides the context within which implementation takes place. By combining UTAUT2, DOI, TOE and Institutional Theory, the framework offers a context-sensitive explanation of AI adoption that accounts for both user-level behaviour and institutional conditions.

7. Conclusion



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