A systematic review of data analytics adoption in faith-based universities in Kenya

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ABSTRACT

This study presents a systematic literature review examining the adoption of data analytics in Faith-Based Universities (FBUs) in Kenya, with emphasis on the role of human capital development (HCD) and institutional readiness. Anchored on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Institutional Theory, the review synthesized evidence from sixty peer-reviewed studies published between 2015 and 2025. Guided by PRISMA protocols and quality-appraised using the Mixed-Methods Appraisal Tool (MMAT), the analysis applied thematic synthesis to capture enablers, barriers, and institutional impacts. Findings reveal that FBUs remain at an early stage of adoption compared to public and private secular universities, constrained by infrastructural deficits, limited digital literacy, financial challenges, and theological caution. Leadership commitment, investment in ICT infrastructure, and cross-institutional collaborations emerged as key enablers, while human capital development was identified as a cornerstone for sustainable adoption. Evidence shows that where analytics were successfully integrated, FBUs experienced gains in student monitoring, institutional planning, regulatory compliance, and governance transparency, especially when aligned with faith-based missions and values. The review concludes that advancing analytics adoption in FBUs requires embedding data use into strategic plans, scaling continuous staff training, and fostering evidence-based cultures that harmonize technological innovation with institutional identity.

Keywords: Adoption of Data Analytics, Human Capital Development, Faith-Based Universities, Institutional Theory

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I. INTRODUCTION

The increasing availability of big data has revolutionized operations and decision-making in higher education institutions (HEIs) worldwide. Data analytics enables universities to monitor student engagement, personalize learning experiences, optimize resource allocation, and support strategic planning. With the advancement of learning management systems (LMS), student information systems (SIS), and predictive analytics tools, HEIs now have unprecedented opportunities to harness data for academic excellence and institutional efficiency (Daniel, 2015; Mohammed,2024; Tsai et al., 2020).

Data analytics plays a pivotal role in improving student performance, enabling early warning systems, and informing pedagogical reforms. In administrative domains, analytics supports budget planning, infrastructure development, and compliance reporting (Mwangi, 2024). Furthermore, data-driven approaches have been linked to improved institutional transparency and accountability (Siemens & Long, 2011). As such, many HEIs in developed countries have embedded analytics into their core operations, transforming them into intelligent, adaptive learning ecosystems.

However, the picture is less optimistic in the global south, where structural challenges such as limited infrastructure, low digital literacy, and funding constraints hinder widespread adoption (Owino, 2023). In Sub-Saharan Africa, HEIs often face technical and organizational obstacles that slow down the uptake of data technologies (Nganga, 2020). Within this broader context, Faith-Based Universities (FBUs) occupy a distinct niche. These institutions combine academic objectives with religious values and governance systems, which shape their receptivity to innovation. FBUs in Kenya often operate autonomously and are not fully integrated into national digital transformation agendas, which further exacerbate their marginalization in policy and practice (Nganga, 2020).

Existing literature acknowledges the transformative potential of data analytics but rarely examines its implementation within the specific context of FBUs (Prinsloo & Kaliisa, 2022). Studies tend to focus on public or large private universities, overlooking the ideological, cultural, and institutional dynamics that influence technology adoption in faith-based settings (Parthe, 2023). While global frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) emphasize perceived usefulness and ease of use, these do not fully capture the organizational conservatism, ethical concerns, or capacity deficits prevalent in FBUs. Similarly, while Institutional Theory helps explain institutional inertia, few studies apply it to understanding resistance in values-driven institutions.

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A significant gap exists in understanding how human capital development (HCD) mediates the relationship between institutional readiness and analytics adoption. Research suggests that staff training, leadership engagement, and capacity-building efforts are critical to successful implementation (Knight et al., 2016; Mbatha et al., 2021). Yet, most FBUs lack structured professional development programs that address digital literacy and analytics competence. Moreover, data governance policies are often underdeveloped, leaving staff and administrators without clear guidelines for ethical and effective data use.

1.1 Statement of the Problem

Although data analytics holds significant potential to transform higher education, FBUs in Kenya continue to lag in its adoption. This slow uptake is attributed to a confluence of challenges related to inadequate digital infrastructure, limited human capacity, and misalignment between institutional cultures and technological innovation. Moreover, FBUs have not benefited from nationwide ICT interventions and lack context-specific frameworks to guide the effective integration of data analytics. The role of human capital development in addressing these deficits remains insufficiently explored. These empirical gaps impede evidence-based policy formulation and practical strategies aimed at fostering digital transformation within FBUs, thereby constituting a critical knowledge gap that this study seeks to address.

1.2 Research Objectives

The specific objectives were to:

i. Assess the current state and patterns of data analytics adoption in higher education institutions, with emphasis on FBUs in Kenya.
ii. Identify key enablers and barriers influencing the adoption of data analytics in FBUs.
iii. Analyze the contribution of human capital development to the adoption and institutionalization of analytics in FBUs.
iv. Explore the institutional outcomes and performance impacts associated with data analytics use in faith-based higher education.
v. Propose practical recommendations for improving data analytics adoption in FBUs through strategic investments in HCD and infrastructure.

II. LITERATURE REVIEW

2.1 Theoretical Review

The adoption and interpretation of data analytics in Faith-Based Universities (FBUs) can best be understood through a multidimensional theoretical lens that integrates both individual and organizational dynamics. This study therefore adopts a hybrid model that combines the Unified Theory of Acceptance and Use of Technology (UTAUT) and Institutional Theory to explain technology adoption within FBUs.

According to Venkatesh et al. (2003), the UTAUT model explicates technology acceptance based on four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs are moderated by demographic factors such as age, gender, and experience. Within the FBU context, performance expectancy reflects how curriculum implementers and administrators perceive the contribution of analytics to improving student performance and institutional planning. Effort expectancy denotes the perceived complexity of using analytics platforms, a challenge often associated with limited exposure and inadequate training. Social influence relates to the effect of peers, institutional leaders, and religious authorities on the decision to adopt technology, while facilitating conditions encompass the availability of supportive infrastructure such as internet connectivity, digital tools, ICT personnel, and enabling institutional policies.

Despite its relevance, the UTAUT framework is primarily individualistic and does not sufficiently consider the wider organizational and cultural contexts that influence technology adoption in FBUs (Aro, 2024). In these institutions, decision-making is not purely rational or individual but is often shaped by collective norms, values, and theological commitments. To address this limitation, the present study incorporates Institutional Theory (DiMaggio & Powell, 1983), which emphasizes the role of coercive, mimetic, and normative pressures in determining organizational behavior and innovation. Coercive pressures arise from external demands such as government regulations, accreditation standards, or donor requirements. Mimetic pressures emerge when institutions emulate the practices of successful peers to maintain legitimacy, while normative pressures stem from the ethical, theological, and professional values embedded within the institutional culture.

Normative pressures are particularly strong in FBUs, where concerns about surveillance, data privacy, and the potential incompatibility of analytics with spiritual or moral principles may lead to hesitation or resistance. These pressures can influence whether institutions embrace or reject emerging technologies. In combining UTAUT and Institutional Theory, this study provides a more comprehensive framework for understanding both individual behavioral

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intentions and organizational efforts to maintain institutional legitimacy. It also highlights the importance of aligning technology adoption strategies with the cultural and religious values of FBUs to ensure meaningful and sustainable digital transformation.

2.1.1 Data Analytics in Higher Education

The rise of data-driven decision-making has transformed HEIs across the globe, creating new opportunities for enhancing teaching, learning, and administrative functions (Ghosh et al., 2024). Data analytics in education is broadly defined as the systematic use of data to generate insights that inform decision-making at individual, institutional, and system levels (Bowers, 2018). It encompasses a range of approaches, including descriptive analytics (summarizing historical data), predictive analytics (forecasting future trends and behaviors), and prescriptive analytics (offering recommendations for action) (Blessing et al., 2025). Together, these approaches allow HEIs to improve efficiency, effectiveness, and accountability.

Data analytics is widely used in the academic field to track student achievement, predict student dropout as well as to design pre-emptive intervention strategies. These types of tools have been used to select at-risk-students that enable proactive assistance to boost retention and completion rates (Larrabee Sonderlund et al., 2018; Selwyn et al., 2016). In learning contexts, analytics embedded in learning management systems (LMS) and student information systems (SIS) generate fine-grained data on student engagement and performance, which can be used to personalize learning pathways, tailor feedback, and guide pedagogical reforms (Johar et al., 2023; Philip and Nyakerario, 2023).

Practically, data analytics is a critical concept of managing and planning the institution outside of the classroom. Some of the functions that analytics assist in on the administrative side would be a budget allocation, infrastructure planning, and compliance reporting (Frempong, 2022). The analytic tools that come to the system present an insight into the enrolment pattern, staff work and functionality to allow the HEIs to match the sources with the institutional priority. To this end, data analytics play an important role not only of quality assurance in academics but also institutional competitiveness in institutions that still experience dynamic environments (Stojanov & Daniel, 2017).

The global economies have made significant progress in using analytics into the sphere of higher education and apply it to their student life-cycle management and monitoring their performance (Larrabee Sonderlund, Hughes & Smith, 2018). However, in Sub-Saharan Africa, the adoption remains low due to infrastructural challenges, digital illiteracy and weak institutional support framework (Mukuni, 2019). Additionally, there has been a history of challenges of governance lapses, lack of leadership support, low development of human capital (Nikita et al., 2024).

Within this broader context, FBUs in Kenya represent a unique case. Their dual mandate of academic and religious objectives, coupled with autonomous governance structures, shapes their readiness to embrace technological innovations. While data analytics could greatly enhance service delivery, student outcomes, and institutional accountability in FBUs, adoption has been hindered by cultural conservatism, inadequate professional development programs, and exclusion from national digital transformation policies (Gkrimpizi et al., 2023). Existing literature tends to overlook these institutions, focusing instead on public or large private universities, leaving a critical gap in understanding the role of data analytics within values-driven higher education settings.

This review therefore situates FBUs within the broader discourse on data analytics in higher education, with particular attention to the mediating role of human capital development in overcoming infrastructural, organizational, and cultural barriers.

III. METHODOLOGY

This study adopted a Systematic Literature Review (SLR) approach grounded in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, rigor, and reliability. The review synthesized peer-reviewed literature on data analytics adoption in higher education, with a specific focus on HCD and institutional performance in FBUs in Kenya. The methodology consisted of a clearly defined search strategy, study selection process, quality appraisal, and thematic synthesis of findings.

3.1 Search Strategy

A search was conducted across six reputable academic databases: Scopus, Web of Science, IEEE Xplore, Google Scholar, Springer Link, and Science Direct. These platforms were selected for their extensive coverage of multidisciplinary peer-reviewed literature, including education, technology, management, and institutional studies. The search focused on studies published between 2015 and 2025 to capture contemporary trends and emerging discourses on analytics in higher education.

To refine the search and ensure relevance, Boolean operators (AND, OR) were applied to formulate targeted queries. Keywords and phrases included combinations such as: ("data analytics adoption" OR "big data in universities") AND ("higher education" OR "faith-based universities"). ("human capital development" OR "staff training" OR

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"capacity building") AND ("data analytics" OR "learning analytics"). ("university performance" OR "decision-making in HEIs") AND ("predictive analytics" OR "data-driven strategies"). The search was limited to English-language articles and prioritized peer-reviewed journal articles, conference papers, and systematic reviews. Grey literature, editorials, and opinion pieces were excluded to maintain scholarly rigor. Reference chaining was also applied to identify relevant studies cited in key articles.

3.2 Study Selection and Quality Evaluation Processes

The study selection followed a structured three-phase process: initial screening, full-text review, and quality assessment. After removing duplicates, all titles and abstracts were reviewed for relevance to the central themes of data analytics, human capital development, and institutional performance within HEIs—specifically faith-based contexts where applicable. Full-text articles were then assessed against inclusion criteria, which required that studies: Be published between 2015 and 2025, Focus on higher education institutions (with preference for or relevance to FBUs), Address data analytics adoption and/or HCD strategies, and be methodologically sound and peer-reviewed.

To ensure quality, selected studies were appraised using the Mixed-Methods Appraisal Tool (MMAT) developed by Hong et al. (2018), which is suitable for evaluating qualitative, quantitative, and mixed-methods research. The MMAT framework assessed relevance, methodological rigor, validity of data collection and analysis, generalizability to FBUs, and source credibility as shown in Table 1. Only studies scoring 60% or above across these criteria were included in the final synthesis, resulting in a corpus of 60 high-quality articles.

Table 1
Appraisal Criteria Based on the Mixed-Methods Appraisal Tool (MMAT)

Criteria	Evaluation Questions
Relevance	Does the study address data analytics adoption in HEIs?
Methodological Rigor	Is the research design appropriate and clearly explained?
Data Validity	Are data collection and analysis methods reliable?
Generalizability	Can the findings be applied to Faith-Based Universities in Kenya?
Publication Type	Is the study published in a peer-reviewed journal or a reputable conference?

Source: (Hong et al., 2018)

3.3 Data Extraction and Analysis

A structured data extraction protocol was employed to capture essential information from each selected study. Extracted data included publication details, study context (country, institutional type, and faith affiliation if any), research objectives, methodology, key findings, challenges identified, and proposed solutions.

Thematic synthesis was used as the analytical approach. This involved coding data from the selected articles and organizing them into key themes and subthemes aligned with the study objectives. Initial codes included terms such as “staff training,” “infrastructure barriers,” “institutional culture,” and “analytics for decision-making.” Through iterative comparison and abstraction, these were grouped into broader thematic categories such as “enablers of adoption,” “barriers and constraints,” “role of HCD,” and “institutional impact.”

Special attention was given to identifying recurring patterns across studies, as well as outliers that offered unique insights into the experiences of FBUs. The synthesis not only summarized findings across contexts but also explored causal relationships, such as how human capital development initiatives influenced adoption outcomes or mitigated resistance in faith-based settings.

Table 2
Summary of Key Themes Identified from the Literature

Theme	Description
Adoption Status	FBUs lag behind in implementing advanced analytics tools
Enablers	Leadership support, infrastructure, policy alignment
Barriers	Poor infrastructure, staff capacity gaps, resistance to change, limited funding
Role of HCD	Critical for skills, leadership development, and long-term sustainability
Institutional Impact	Gains in student performance, planning, and compliance where analytics are well-integrated

To enhance transparency, the study selection process was visualized using a PRISMA flow diagram as shown in Figure 1. The diagram outlines the number of records identified, screened, assessed for eligibility, and ultimately included, providing a visual summary of the methodological rigor applied.

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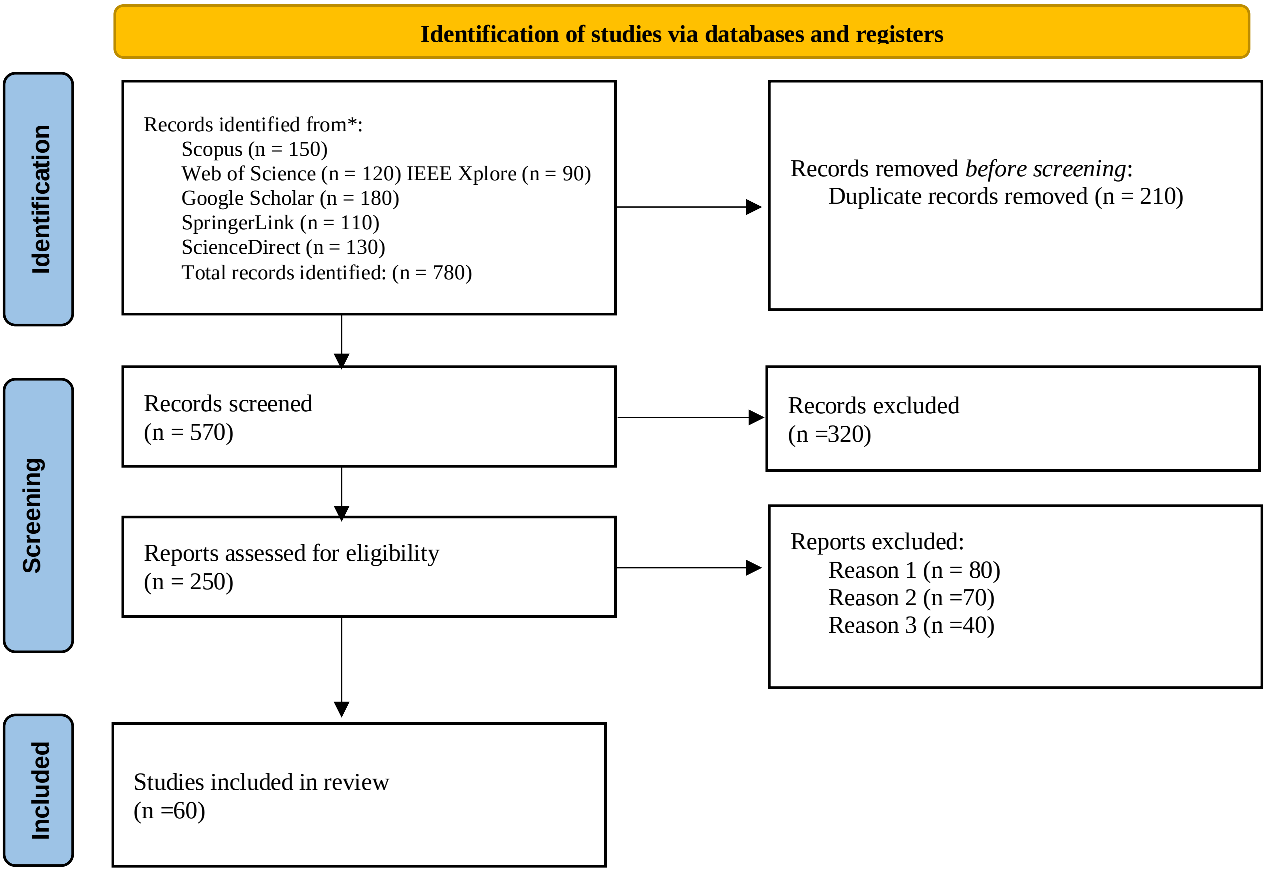

Figure 1
A PRISMA Diagram Visualizing the Study Selection Process
Source : Page et al. (2021)

IV. FINDINGS & DISCUSSION

4.1 Response Rate

The systematic review of sixty studies revealed important insights into the adoption of data analytics in FBUs in Kenya, with particular focus on the role of HCD and institutional readiness. Findings are presented thematically, reflecting the key categories identified in the synthesis: adoption status, enablers, barriers, role of HCD, and institutional impacts.

4.1.1 Adoption Status

The evidence indicates that while data analytics is increasingly recognized in higher education globally, FBUs in Kenya remain at an early stage of adoption. Studies show that public and private secular universities have advanced further in implementing analytics for student retention, curriculum planning, and institutional reporting (Gamede, Ajani & Afolabi, 2021; Siemens & Long, 2011; Bai et al., 2021). By contrast, FBUs lag behind, often due to limited exposure, weaker digital infrastructure, and theological caution toward technological innovations (Smith, 2017; Wango, 2017). Case studies from Kenya and Sub-Saharan Africa suggest that FBUs are aware of the potential of analytics but lack structured policies or frameworks for integration (Wekesa, 2024; Matere, 2024). Similar patterns are observed in other African contexts, where institutions struggle to balance tradition with digital transformation imperatives (Gbadebo, 2024; Kamau, 2020).

4.1.2 Enablers of Adoption

Leadership commitment emerged as a strong determinant of adoption. Institutions where senior leaders championed digital transformation and aligned analytics initiatives with mission-driven goals recorded better progress (Adeniran et al., 2024; Coolen et al., 2023). Infrastructure investment—particularly in learning management systems, digital literacy programs, and governance frameworks—was also identified as a key enabler (Santiago Rivera & Shanks, 2015; UNESCO, 2021; UNESCO, 2022). Cross-institutional collaborations and mentorship arrangements, for example between public universities and FBUs, created opportunities for shared learning and reduced the cost of implementation

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(Gbadebo, 2024; Prabowo & Bandur, 2022). Recent evidence suggests that peer-learning networks in Kenya and Uganda have encouraged FBUs to cautiously experiment with analytics integration (Wekesa, 2024).

4.1.3 Barriers and Constraints

Several barriers were recurrent across studies. Poor ICT infrastructure and unreliable internet access were consistently cited as limiting adoption, particularly in faith-based and rural-based universities (Mbatha, Ngcobo & Mhlongo, 2021; Okwako, 2020). The gap in staff capacity also featured prominently, where most of the academic and administrative staff members did not have the technical knowledge and digital literacy needed (Mokhtari, 2023; Tenya, Maina & Awuor, 2024). The adoption was further limited by institutional resistance, with a basis in either theological issues or fear of surveillance (Jones et al., 2020; Smith, 2017). There was also a constraint in finances whereby investments could not be made on advanced tools, including predictive analytics, big data platforms (Alsheikh, 2018; Adepoju and Pub, 2025). Moreover, there were contextual impediments contributing to those problems, including bureaucratic governments and insufficient donor attention to FBUs (Nikita et al., 2024).

4.1.4 Role of Human Capital Development

Human capital development was consistently identified as a cornerstone for sustainable adoption. Studies highlighted the importance of continuous staff training in analytics tools, data ethics, and pedagogical applications (Anthun & Håland, 2024; Mokhtari, 2023). Leadership development programs were also critical, as institutions with trained leaders who understood both theological contexts and digital trends were more likely to adopt analytics meaningfully (Njenga, 2016; Kamau, 2020). Case-specific findings from FBUs in Kenya revealed that when staff received targeted capacity-building in digital literacy, resistance decreased and adoption accelerated (Wekesa, 2024; Matere, 2024). Scholars emphasize that HCD is not only a technical necessity but also a cultural bridge in religious contexts, as it facilitates alignment between data-driven approaches and theological values (Knight et al., 2016; Tenya, Maina & Awuor, 2024).

4.1.5 Institutional Impacts

Where data analytics was successfully integrated, institutions reported measurable benefits. Positive outcomes included improved student performance monitoring, enhanced planning and resource allocation, and better compliance with regulatory requirements (Al-Zahrani & Alasmari, 2023; Sithumini et al., 2024; Wilbrod et al., 2024). In some cases, analytics supported personalized learning pathways that increased student engagement (Khor & K, 2023; Shete et al., 2024). Evidence also suggests that analytics use strengthened accountability and transparency in institutional governance, contributing to both academic and ethical excellence (Ahmed et al., 2024; Adepoju & Pub, 2025). Early adopters among Kenyan FBUs demonstrated that aligning analytics with faith-based values and mission statements increased legitimacy and stakeholder acceptance (Matere, 2024; Wekesa, 2024.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The findings show that although FBUs in Kenya have identified the importance of data analytics in enhancing student engagement, academic excellence, and administration, adoption is still hampered by institutional constraints, ineffective digital literacy levels, and the appropriateness of technological solutions within a theological and ethics-oriented clothesline. An analysis of sixty academic publications supported the notion that effective implementation of analytics in higher education necessitates effective leadership, sufficient resources and structures that are institutionally appropriate and specific to context.

5.2 Recommendations

To overcome these barriers, FBUs should integrate analytics into strategic planning, invest in continuous staff training, and foster a culture of evidence-based decision-making.

REFERENCES

Adeniran, I., Efunniyi, C., Osundare, O., & Abhulimen, A. (2024). Integrating data analytics in academic institutions: Enhancing research productivity and institutional efficiency. *International Journal of Scholarly Research in Multidisciplinary Studies, 5*(1), 77–87. https://doi.org/10.56781/ijsrms.2024.5.1.0041

Adepoju, A., & Pub, A. (2025). A data governance framework for high-impact programs: Reducing redundancy and enhancing data quality at scale. *International Journal of Multidisciplinary Research and Growth Evaluation, 4*(1), 1141–1154.

Licensed Under Creative Commons Attribution (CC BY-NC)

Ahmed, J., Kathambi, B., & Robert, K. (2023). Barriers to community participation in governance standards setting for sustainable mangrove management in Lamu County. *Open Journal of Forestry, 13*(4), 353–367. https://doi.org/10.4236/ojf.2023.134021

Alsheikh, M. (2018). Challenges facing big data adoption in developing countries' higher education. *International Journal of Information and Communication Technology Education, 14*(3), 22–34.

Al-Zahrani, A., & Alasmari, T. (2023). Learning analytics for data-driven decision making: Enhancing instructional personalization and student engagement in online higher education. *International Journal of Online Pedagogy and Course Design, 13*(1), 1–18. https://doi.org/10.4018/IJOPCD.331751

Anthun, K., Håland, E., et al. (2024). What influences the use of HR analytics in human resource management in Norwegian municipal health care services? *BMC Health Services Research, 24*, 1131. https://doi.org/10.1186/s12913-024-11610-y

Aro, O. (2024). Predictive analytics in financial management: Enhancing decision-making and risk management. *International Journal of Research Publication and Reviews, 5*(10), 2181–2194. https://doi.org/10.55248/gengpi.5.1024.2819

Bai, X., Zhang, F., Li, J., Guo, T., Aziz, A., Jin, A., & Xia, F. (2021). Educational big data: Predictions, applications, and challenges. *Big Data Research, 26*, 100270. https://doi.org/10.1016/j.bdr.2021.100270

Bowers, A. J., Choi, Y., Shi, H., Sun, F., Sun, H., Williams, J., & Weeks, S. (2022). Mapping 16 equity indicators to the New York City schools public datasets: Access, opportunity, and outcomes. Teachers College, Columbia University.

Coolen, P., Heuvel, S., Voorde, K., & Paauwe, J. (2023). Understanding the adoption and institutionalization of workforce analytics: A systematic literature review and research agenda. *Human Resource Management Review, 33*(4), 100985. https://doi.org/10.1016/j.hrmr.2023.100985

Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology, 46*(5), 904–920.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review, 48*(2), 147–160.

Frempong, D., Akinboboye, O., Okoli, I., Afrihyia, E., Umar, M., Umana, A., Appoh, M., & Omolayo, O. (2022). Real-time analytics dashboards for decision-making using Tableau in public sector and business intelligence applications. *Journal of Frontiers in Multidisciplinary Research, 3*, 65–80. https://doi.org/10.54660/.IJFMR.2022.3.2.65-80

Gamede, B., Ajani, O., & Afolabi, O. (2021). Exploring the adoption and usage of learning management systems as an alternative for curriculum delivery in South African higher education institutions during COVID-19 lockdown. *International Journal of Higher Education, 11*(1), 71–81. https://doi.org/10.5430/ijhe.v11n1p71

Gbadebo, A. (2024). Digital transformation for educational development in Sub-Saharan Africa. *International Journal of Social Science and Religion, 5*(3), 397–418. https://doi.org/10.53639/ijssr.v5i3.262

Ghosh, P., Sharma, A., Sharma, K., Priya, P., & Prasad, S. (2024). Harnessing AI for organizational excellence: Interdisciplinary strategies for enhancing marketing, HR, and financial performance through data-driven decision-making. *European Economics Letters, 14*(2), 632–640.

Gkrimpizi, T., Peristeras, V., & Magnisalis, I. (2023). Classification of barriers to digital transformation in higher education institutions: Systematic literature review. *Education Sciences, 13*(7), 746. https://doi.org/10.3390/educsci13070746

Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M.-P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M.-C., & Vedel, I. (2018). Mixed methods appraisal tool (MMAT), version 2018, user guide. McGill. http://mixedmethodsappraisaltoolpublic.pbworks.com

Johar, N. A., Kew, S., Tasir, Z., & Koh, E. (2023). Learning analytics on student engagement to enhance students' learning performance: A systematic review. *Sustainability, 15*(10), 7849. https://doi.org/10.3390/su15107849

Jones, K., Asher, A., Goben, A., Perry, M., Salo, D., Briney, K., & Robertshaw, M. (2020). "We're being tracked at all times": Student perspectives of their privacy in relation to learning analytics in higher education. *Journal of the Association for Information Science and Technology, 71*(9), 1048–1059. https://doi.org/10.1002/asi.24358

Khor, E., & Mutthulakshmi, K. (2023). A systematic review of the role of learning analytics in supporting personalized learning. *Education Sciences, 14*(1), 51. https://doi.org/10.3390/educsci14010051

Knight, S., Buckingham Shum, S., & Littleton, K. (2016). Epistemology, pedagogy, assessment, and learning analytics. *Journal of Learning Analytics, 3*(2), 187–210.

Larrabee Sonderlund, A., Hughes, E., & Smith, J. (2018). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology, 50*(5), 2594–2618. https://doi.org/10.1111/bjet.12720

Mbatha, B., Ngcobo, S., & Mhlongo, B. (2021). Exploring educators' readiness for digital transformation in rural-based universities. *South African Journal of Higher Education, 35*(6), 112–128.

Licensed Under Creative Commons Attribution (CC BY-NC)

Mohammed, M. S. (2024). Review of literature on the use of learning analytics and learning analytical dashboards in improving student performance in higher education institutions in Kenya. *International Journal of Research and Innovation in Applied Science, 9*(5).

Mokhtari, F. (2023). Fostering digital literacy in higher education: Benefits, challenges, and implications. *International Journal of Linguistics, Literature, and Translation, 6*(10), 160–167. https://doi.org/10.32996/ijllt.2023.6.10.19

Mukuni, J. (2019). Challenges of educational digital infrastructure in Africa: A tale of hope and disillusionment. *Journal of African Studies and Development, 11*(7), 59–63. https://doi.org/10.5897/JASD2019.0539

Mwangi, J. (2024). Impact of digital learning tools on student performance in Kenya. *African Journal of Education and Practice, 9*, 13–22. https://doi.org/10.47604/ajep.2521

Nikita, N. A., Azim, K. S., Jafor, A., Shayed, A. U., Hossain, M. A., & Khan, O. U. (2024). Digital transformation in non-profit organizations: Strategies, challenges, and successes. *Advanced International Journal of Multidisciplinary Research, 2*, 13–20.

Njenga, M. (2016). Effects of change management strategy on performance in public universities in Kenya: The case of the Technical University of Kenya. *Strategic Journal of Business & Change Management, 3*(2). https://doi.org/10.61426/sjbcm.v3i2.260

Odengo, R., Bula, H., & Kiiru, D. (2022). Moderating effect of human resource policies on balanced contract and performance of academic staff in selected public universities. *Journal of Human Resource and Leadership, 7*(1), 94–106. https://doi.org/10.47604/jhrl.1646

Okwako, W. (2020). Institutional barriers to ICT integration in teaching: A study of selected private universities in Kenya. *International Journal of Education and Development Using Information and Communication Technology, 16*(3), 80–98.

Owino, B. (2023). Adoption of e-learning in universities in Kenya and its effect during COVID-19 (Master's thesis). United States International University - Africa. USIU-Africa Repository.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews**.** *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Parthe, R. (2023). Comparative analysis of data visualization tools: Power BI and Tableau. *International Journal of Scientific Research in Engineering and Management, 7*(7), 1–11. https://doi.org/10.55041/IJSREM26272

Philip, J., & Nyakerario, F. (2023). Blended learning: Threats and hurdles in developing countries—A case study of Nigeria and Kenya. *Greener Journal of Social Sciences, 13*(1), 151–158. https://doi.org/10.15580/gjss.2023.1.112024176

Prabowo, H., & Bandur, A. (2022). Digital transformation in higher education: Global trends and future research directions. *Journal of Innovation in Business and Economics, 5*(2), 77–90. https://doi.org/10.22219/jibe.v5i02.21218

Prinsloo, P., & Kaliisa, R. (2022). Learning analytics on the African continent: An emerging research focus and practice. *Journal of Learning Analytics, 9*(2), 1–12.

Santiago Rivera, D., & Shanks, G. (2015). A dashboard to support management of business analytics capabilities. *Journal of Decision Systems, 24*(1), 73–86.

Selwyn, N., Henderson, M., & Chao, S.-H. (2016). 'You need a system': Exploring the role of data in the administration of university students and courses. *Journal of Further and Higher Education, 42*(5), 1–11. https://doi.org/10.1080/0309877X.2016.1206852

Shete, S., Koshti, P., & Pujari, V. (2024). The impact of AI-powered personalization on academic performance of students. In *2024 International Conference on Recent Trends in Computational Science and Technology (ICRTCST)* (pp. 295–301). IEEE. https://doi.org/10.1109/ICRTCST61793.2024.10578480

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30–32.

Sithumini, J. H. C., Sanjuka, A. N. E., Ranawaka, P. S., Hasaranga, H. G. D., Samarakkody, T., & Pathirana, G. (2024). Systematic review: The role of data analytics in enhancing academic performance, classroom interaction, and learning analytics in higher education. In *Proceedings of the 3rd International Conference on Sustainable & Digital Business (ICSDB 2024)* (p. 168).

Smith, A. (2017). Theological barriers to innovation in faith-based institutions. *Christian Higher Education, 16*(1–2), 90–105.

Stojanov, A., & Daniel, B. K. (2024). A decade of research into the application of big data and analytics in higher education: A systematic review of the literature. *Education and Information Technologies, 29*, 5807–5831. https://doi.org/10.1007/s10639-023-12033-8

The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. (2021). *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

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Tsai, Y. S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2020). Complexity leadership in learning analytics: Drivers, challenges, and opportunities. *British Journal of Educational Technology, 51*(6), 1339–1354.

UNESCO. (2021). *Digital transformation of education: Systemic approaches for developing digital education policies*. UNESCO Publishing.

UNESCO. (2022). *Using learning assessment data for educational planning: A resource for Sub-Saharan Africa*. UNESCO Digital Library. https://unesdoc.unesco.org/ark:/48223/pf0000382621

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Wekesa, M., Ikoha, A., & Wechuli, A. (2023). Readiness for adoption of learning analytics to support technology-enabled learning in universities in Kenya. *International Journal of Innovative Science and Research Technology, 8*, 1254.

Wilbrod, M., Joshua, T., & Research Repository Extension, A. I. U. (2024). Data-driven approaches to enhancing student retention in higher education: A case study of Avance International University. *International Journal of Higher Education, 10*(2), 43–51.

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