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Usage of Data Analytics to Track University Students' Performance in Africa: A Scoping Review

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Abstract

Using data analytics to analyse university student performance in Africa is an attractive potential, given that the continent's institutions face unique problems such as enormous student populations, various educational backgrounds, and varying levels of funding. However, using data analytics can dramatically increase academic performance and institutional effectiveness. The increasing availability of educational data, as well as advancements in data analytics, have opened up new prospects to optimise academic performance tracking in Higher Education Institutions (HEIs). This scoping re-view paper investigates the use of data analytics to track and enhance university student performance across African institutions. The study synthesises findings from peer-reviewed studies published between 2010 and 2025, with an emphasis on techniques, tools, implementation contexts, and results. The paper emphasises the widespread use of Machine Learning (ML) models, predictive analytics, and Learning Management Systems (LMSs) for identifying at-risk students, understanding learning behaviours, and informing institutional decisions. It also uncovers challenges specific to the African context, including data quality, technological infrastructure, and policy limitations. The findings highlight the potential of data-driven approaches to support student success but emphasise the need for localised strategies and capacity building. This review contributes to a growing body of knowledge on educational data analytics and provides a foundation for future research and practice in African HEIs. The future research should focus more on expanding the research depth, real-world applications, interdisciplinary integration, and addressing contextual challenges related to the use of data analytics to track African university students.

Keywords: At-risk students, data analytics, educational insights, ICT, machine learning, learning analytics.

Introduction

Higher Education Institutions (HEIs) across Africa are currently navigating a transformative phase discernable by a convergence of demographic shifts, technological advancements, and ongoing policy reforms (Ahmad, 2024; Daniels & Gebhardt, 2021; Woldegiorgis, 2022). Matsieli and Mutula (2024) highlight that this transformation is taking place amid considerable structural and systemic challenges. These include escalating student enrolments, constrained financial resources, infrastructural insufficiencies, and disparities in student preparedness. As African HEIs endeavor to address these pressures while preserving academic quality and institutional effectiveness, data analytics has emerged as a promising avenue. It plays a pivotal role in enhancing educational outcomes and informing administrative decision-making (Mpofu & Chasokela, 2025).

A host of researchers (Alalawi, Athauda & Chiong, 2024; Foster & Siddle, 2020; Larrabee Sønderlund et al., 2022; Hughes & Smith, 2019; Russell, Smith & Larsen, 2020; and Wong & Li, 2020) highlighted that the recent developments denote that data analytics, particularly in the form of Learning Analytics (LA), is being increasingly recognised for its potential to monitor students' learning behaviors. Furthermore, it predicts academic performance, and facilitate timely

interventions for at-risk students. Empirical studies (Asogwa, Asogwa & Chinedu, 2023; Badaru & Adu, 2022; Dake & Buabeng-Andoh, 2022; Elbouknify et al., 2025; Mduma, Kalegele & Machuve, 2019; Prinsloo & Kaliisa, 2022; and Wandera, Marivate & Sengeh, 2020), from diverse African contexts demonstrate the growing relevance and impact of such approaches. For instance, predictive models employing Machine Learning (ML) algorithms, particularly Random Forests (RF), have demonstrated over 90% accuracy in detecting students at risk of attrition within Ghanaian institutions. Comparable initiatives in South Africa, Sierra Leone, Morocco, Nigeria, Kenya, and Tanzania illustrate the diverse yet converging patterns of LA adoption across Africa. According to Lourens and Bleazard (2016), one of the most common applications of data analytics in African HEIs is the use of predictive models to identify at-risk students. These systems use historical academic data, attendance records, and online activity to predict student outcomes and intervene before failure occurs (Bin Mat et al., 2013; Gray & Perkins, 2019). For instance, studies from South Africa and Nigeria (Mbuvha et al., 2021; Asogwa et al., 2023) highlight the successful deployment of Logistic Regression (LR) and Decision Trees (DT) models to forecast academic success and dropout likelihood. The academic evidence from Ghana, South Africa, and broader Sub-Saharan contexts robustly supports the deployment of predictive analytics and early warning systems within African universities (Ogundaini & Mlitwa, 2023; Prinsloo & Kaliisa, 2022b; Tahiru, 2023). Cele (2021) suggests that these systems show high predictive accuracy and practical value for student retention and success. However, their sustainable implementation still pivots on addressing contextual challenges, particularly around data governance, tool integration, infrastructure, and professional capacity.

Prinsloo and Kaliisa (2022) suggest that these initiatives, though promising, remain unequal in their implementation and maturity in African universities' context. Some South African universities, including the Cape Peninsula University of Technology (CPUT) (Ngqulu, 2020) and the University of South Africa (UNISA), have started using predictive tools in their academic support systems. However, many others still rely on basic Learning Management System (LMS) data, limited by technical, governance, and ethical challenges. According to Asamoah and Amarteifio (2025), African HEIs must contend with the contextual complexities inherent in applying data analytics across heterogeneous educational environments. Socio-economic disparities, constrained digital access, and varying institutional capacities collectively shape the efficacy and suitability of analytics-driven interventions. Guided by the Population Concept Context (PCC) framework, this review will answer the following main research question: How is data analytics being used to track and support university students' performance in African HEIs? The subsidiary re-search questions include:

- What types of data analytics approaches are being implemented in African HEIs?
- What indicators are used to measure student performance?
- What challenges and opportunities are identified in using data analytics for student success in this context?

This paper presents a Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) framework as proposed by Tricco et al. (2018) to report on how data analytics is being utilised across African HEIs to monitor and enhance student performance. By synthesising current literature and case studies, it aims to examine the tools, techniques, institutional contexts, and educational out-comes associated with these efforts. In doing so, it highlights both the opportunities and limitations inherent in applying data analytics in African HEIs and proposes di-rections for future research and practice. The study begins with the literature search descriptions. Secondly, it summarises the review's results. Thirdly, it provides the discussions of the reviewed studies, and finally propose recommendations and draws the conclusions.

Literature search

Search Strategy

The current review study adheres to a scoping review methodology, which is systematically identifies and synthesises relevant peer-reviewed literature from the date range of 2010 to 2025. Subsequently, the researcher developed the following search query to identify relevant articles, using the key words such as ("data analytics," OR “learning analytics” OR "student performance," OR "higher education,") AND ("Africa"). Academic databases including Scopus, Web of Science, and Google Scholar were extensively searched using keywords. The researcher conducted a scoping review search between 13 March to 30 July 2025. Figure 1 shows an example of a screenshot of this study’s ‘keyword search’ process following the PRISMA-ScR protocol.

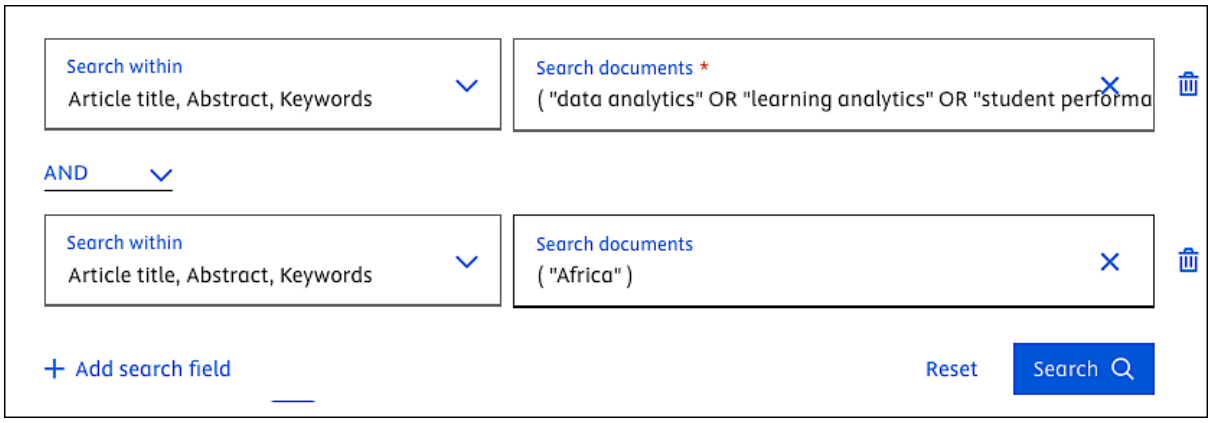

Figure 1: A screenshot example of the search query (executed in Scopus).

A Microsoft Excel spreadsheet was developed where all the retrieved materials were recorded for further screening, analysis, and screening assessment. Regarding the use of inclusion and exclusion criterions, studies that were included are those focused on African HEIs, employed data analytics in academic performance tracking, and were published in English. The studies that were excluded are those that were published before the year 2010, as well as letters to the editor and articles that were not authored in English and had no connections to data analytics in academic performance tracking in the context of African HEIs. This study adopted a scoping review approach, guided by the PRISMA-ScR framework (Tawfik et al., 2019; Tricco et al., 2018). This approach was appropriate for mapping the extent, range, and nature of research evidence on the use of data analytics in African HEIs, rather than assessing the quality or effectiveness of interventions, which is typically the focus of systematic reviews. Thus, in the current study, PRISMA-ScR, as depicted in Figure 2, facilitated the identification and inclusion of the pertinent literature. In this study, a comprehensive analysis was conducted on a total of 236 papers to fulfil the objectives of this research.

Data Extraction and Quality Assessment

The scoping review followed a rigorous process of data extraction and quality assessment, structured according to the PRISMA-ScR guidelines. The initial identification of studies involved comprehensive searches across three electronic data-bases: Scopus (n = 320), Web of Science (WoS) (n = 71), and Google Scholar (n = 149), yielding a total of 540 records. All identified citations were imported into EndNote 8 reference management software to facilitate the removal of duplicates. This process resulted in the exclusion of 304 duplicate records, leaving 236 articles for further screening based on titles and abstracts. Following this screening stage, 123 studies were excluded due to irrelevance to the review objectives.

Subsequently, 113 full-text articles were retrieved and assessed for eligibility. During this

phase, 88 studies were excluded for the following reasons: lack of relevance to the research questions (n = 45), duplication (n = 29), and unavailability of the full-text (n = 14). In addition to the database searches, a manual search was conducted, which yielded an additional eight relevant studies. As a result, a total of 23 studies met the inclusion criteria and were incorporated into the qualitative synthesis. Of these, 21 studies were deemed to meet the methodological standards required for inclusion in the network and meta-analysis. The entire selection process ensured a systematic, transparent, and reproducible approach to identifying high-quality evidence for synthesis.

The exclusion of studies not directly related to the objectives of this scoping re-view was guided by the application of pre-established inclusion and exclusion criteria. Specifically, studies were excluded if they did not address the core research questions, lacked empirical data, or fell outside the scope of the review's thematic focus. This included studies that were conceptually unrelated, presented anecdotal evidence without methodological rigor, or focused on populations, settings, or outcomes that were not aligned with the purpose of the review. Furthermore, duplicate publications, inaccessible full-texts, and articles that did not meet the quality thresholds for methodological transparency were excluded during the screening and eligibility stages. These exclusion decisions were essential to maintain the scientific integrity, relevance, and analytical coherence of the review, and to ensure that only high-quality, contextually appropriate evidence informed the qualitative synthesis and meta-analysis.

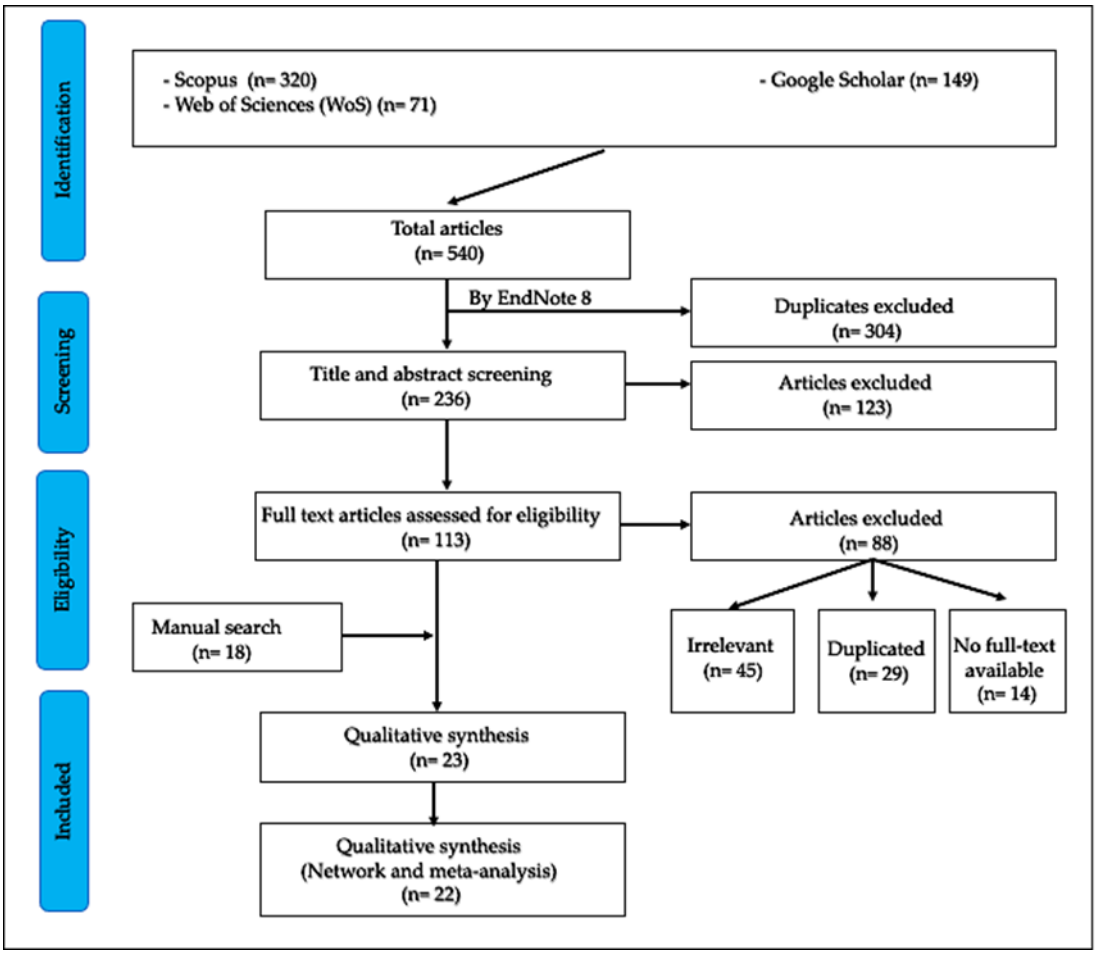

Figure 2: PRISMA-ScR flow diagram of studies' screening and selection (adopted from Tawfik et al., 2019).

Results

Applications of Data Analytics in African Universities

The selected studies in Appendix 1. collectively affirm the growing adoption and impact of ML and LA in African educational contexts. While predictive accuracy remains an important focus, equally significant are the institutional, infrastructural, and pedagogical dimensions shaping the success of these technologies (Aithal, Prabhu & Aithal, 2024; Williamson, 2016). Key challenges, such as limited datasets, inadequate technological infrastructure, and privacy concerns, continue to affect the adoption of ML and LA in African universities. These challenges highlight the need for more localised research, interdisciplinary collaboration, and stronger policy support to fully harness the potential of these technologies (Prinsloo & Kaliisa, 2022). The reviewed body of literature in Appendix 1. reveals a growing interest in the application of ML and LA to address educational challenges in African HEIs. These studies span various methodological approaches, regional contexts, and educational goals, highlighting the diversity and potential of ML and LA in improving student out-comes and institutional performance. While several studies applied data analytics primarily for early warning systems (e.g., identifying at-risk students), these implementations reflect the LA cycle proposed by Siemens (2013), where data collection, analysis, and feedback inform pedagogical decisions. However, few studies demonstrated the closing of the feedback loop, a gap that suggests limited translation of analytics insights into actionable interventions. The summary of reviewed studies that were included for qualitative synthesis and meta-analysis are presented in Appendix 1.

Predictive modeling of student performance and dropout is a recurring theme across multiple studies. For instance, in Ghana, Dake and Buabeng Andoh (2022) employed ensemble methods such as RF, Support Vector Machines (SVM), and DT, achieving approximately 70% accuracy in predicting student dropout. Similarly, Asogwa et al. (2023) in Nigeria reported RF accuracies of up to 79.45% for predicting student attrition. In a more advanced implementation, Elbouknify et al. (2025) in Morocco applied RF and Gradient Boost (XGBoost) to secondary education data, achieving predictive accuracies close to 88%, indicating the feasibility of early detection frameworks across educational levels.

Cross-national and interpretive approaches were also observed. Wandera et al. (2020) examined educational datasets from South Africa and Sierra Leone using RF and Shapley Additive Explanations (SHAP) for interpretability, focusing on comparative analytics. Abuodha et al. (2024) propose a ML–driven framework for adaptive LMS within Kenyan higher education. Although still in the conceptual stage, the study emphasises the importance of dynamic content delivery tailored to learner profiles. The proposal envisions an adaptive LMS capable of improving personalisation through ML algorithms, with the goal of enhancing learner engagement and academic outcomes. Maqoqa (2025) advances the discourse by focusing on the integration of Artificial Intelligence (AI) and LA within South African institutions. Drawing on institutional data, the study centers on governance frameworks necessary for the ethical and effective implementation of AI/LA systems. The research highlights the need for robust policy and oversight structures to manage risks related to data privacy, algorithmic bias, and institutional accountability. Ngary and Twum-Darko (2024) provide a theoretical examination of ML and big data applications in South Africa, specifically aiming to construct a conceptual framework for academic and psycho-socio analytics. Using secondary data, their work emphasises performance enhancement by integrating socio-emotional indicators with academic metrics. This framework proposes a holistic approach to learner profiling, recognising the multidimensional factors influencing student success.

Ogundaini and Mlitwa (2023) conduct a literature-based meta-analysis of LA research across Sub-Saharan Africa, drawing primarily from conference proceedings. Their study critiques the prevailing focus on performance metrics, advocating for a broader conceptualisation of LA that includes

developmental, behavioral, and affective dimensions. The analysis suggests that existing research underrepresents the diverse ways in which LA can support educational equity and learner agency. Several studies adopted qualitative or hybrid methodologies to explore LA in broader institutional contexts. Prinsloo and Kaliisa (2022) conducted a scoping review on data privacy issues in LA, while Maluleke (2024) employed a PRISMA-based systematic review to synthesise findings on LMS adoption across African HEIs, noting significant correlations between student engagement and academic performance. Maluleke (2023) further contributed conference-based insights on the emergence of learning engagement clusters and the efficacy of LA-driven interventions.

Tanzania-based studies emphasised both primary and tertiary education. Mduma et al. (2019) applied ML techniques DT, Artificial Neural Network (ANN), Deep Neural Network (DNN) to early education data, while Mtebe and Mwalumbwe (2017) analysed Moodle-based analytics at Mbeya University for contextual insights. Similarly, Okewu (2017) focused on LMS data mining in Nigeria, though without reporting specific model accuracies.

A notable development is the integration of mobile LA. Mgeni et al. (2024) surveyed 240 students from the State University of Zanzibar (SUZA) and found that 57% cited unreliable internet and device incompatibility as major barriers to mobile LMS adoption. This highlights infrastructural challenges unique to the African context.

Studies from South Africa, such as the UNISA case study (2019) and Simelane & Mnisi (2023), employed system log data and educator interviews, respectively, to assess engagement via LMS tools like forums and dashboards. The work of Badaru & Adu (2022) similarly documented the prevalence of Moodle and Blackboard in South African universities, linking LMS use to improved course facilitation. Finally, Ngulube and Ncube (2025) conducted a systematic review of User Experience (UX) challenges in LMS platforms across African HEIs, identifying recurring issues in usability and accessibility that may hinder LA adoption and impact.

Challenges of Data Analytics Implementation in African Universities

The adoption of LA in African HEIs is progressing but remains imbalanced and constrained by systemic barriers (Mugimu, 2021). Therefore, Macfadyen et al. (2014) and Alzahrani et al. (2023) believes that addressing these challenges will require a coordinated strategy encompassing capacity building, infrastructural investment, policy reform, and stakeholder engagement. Without these foundational supports, the transformative potential of analytics in African HEIs may remain largely unrealised (Rambe & Moeti, 2017). Despite growing interest in data-driven decision-making and LA within African HEIs, the effective implementation and institutionalisation of these practices face numerous structural and contextual challenges.

Data quality and availability is a major impediment to effective analytics adoption. In Africa, there is a fragmented nature of student data across many institutions (Klein et al., 2019). Paik et al. (2019) postulate that inconsistent data entry practices, the absence of centralised data management systems, and incomplete academic records undermine the reliability and utility of analytical outputs. These data quality issues pose significant limitations for predictive modeling and evidence-based interventions (Kappen et al., 2018). With regards to technological infrastructure and funding constraints, Ntorukiri, Kirugua and Kirimi (2022) point out that many African universities operate in environments characterised by inadequate Information and Communication Technology (ICT) infrastructure, limited bandwidth, unreliable internet connectivity, and insufficient computing resources. The uneven implementation of LMSs, particularly in under-resourced institutions, exacerbates these challenges (Mahama, Amankwah-Sarfo & Gyedu, 2024). Furthermore, constrained funding restricts the capacity to acquire or maintain modern analytics platforms, hindering long-term HEIs commitment (Klein et al., 2019; Singun, 2025).

Most of African HEIs significantly lack or do not have an institutional policy governing

data privacy, security, and ethical use (Prinsloo & Kaliisa, 2022). This is major challenge which still remain underdeveloped across many HEIs. Giuffrida and Hall (2023) indicate that issues of student consent, regulatory compliance, and the responsible use of personal data often go unaddressed, impeding the formal integration of LA tools. Institutions such as UNISA have initiated LA pilots but continue to grapple with questions of data integrity and governance (Toi, 2019). The shortage of skilled personnel with expertise in educational data science and analytics is a critical bottleneck (Nwokeji et al., 2019; Osman & Anouze, 2016). According to Corral de Zubielqui et al. (2015), many HEIs lack in-house capacity to design, implement, and interpret data analytics models, leading to reliance on external consultants. This outsourcing approach is often financially unsustainable and limits institutional learning and self-reliance.

Maluleke (2024) indicates that several LA initiatives remain at a nascent stage, frequently focusing on rudimentary indicators such as login frequencies or resource downloads. As observed in the Tanzanian context by Mgeni et al. (2024), such surface-level metrics may not yield meaningful insights into actual learning behaviors or outcomes, thereby reducing their pedagogical value. Successful implementation of LA requires active involvement and trust from academic staff (Jackson, 2021). However, many faculty members express skepticism about the relevance of analytics to teaching and learning. Authors such as Ahn et al. (2019); McKenney; Mor (2015); and Qazi and Pachler (2025) unanimously agree that there is a clear need for professional development, mentorship, and institutional support to help educators interpret analytics dashboards and integrate data insights into instructional design.

Contextual Considerations and Localised Strategies

The successful adoption of data analytics in African HEIs pivots on the recognition and integration of contextual factors unique to the region (Maluleke, 2024). Mithun and Roopadarshini (2024) suggest that the localised strategies, particularly those that prioritise simplicity, mobile access, and regional collaboration, offer a viable pathway for advancing LA in a way that is inclusive, sustainable, and pedagogically meaningful. According to Ul Hassan, Murtaza and Rashid (2025), the effective integration of data analytics in African HEIs necessitates a deliberate alignment with local socio-economic, technological, and cultural contexts. Unlike high-income countries where analytics systems are often built on mature digital infrastructure and standardised data practices, African institutions face distinct constraints that demand tailored approaches (Pisa et al., 2020).

Son, Park and Park (2017) argue that a key consideration is the variability in digital literacy, language proficiency, and access to personal digital devices among students. Metrics traditionally used to gauge engagement, such as time spent on learning platforms or number of logins, may not accurately reflect student effort or learning potential in these settings (Hussain et al., 2018). As such, Prinsloo and Kaliisa (2024c) aver that analytics models must be recalibrated to reflect the lived realities of students and educators in diverse African contexts.

To address these challenges, localised strategies should be proposed and, in some cases, implemented with success. For instance, there is a dire need for a simplified analytics models as a strategy which can be useful for institutions at an early stage of data maturity, basic descriptive analytics and low-complexity models may be more appropriate than advanced predictive algorithms (Slavakis, Giannakis & Mateos, 2014). This ensures that institutions can derive meaningful insights without requiring extensive technical infrastructure or expertise. Another strategy can be mobile-friendly platforms, given the widespread use of mobile devices as primary access points for digital content, developing analytics tools that are optimised for mobile use is critical (Evanick 2024). Mobile platforms can not only enhance student engagement but also facilitate continuous data collection in low-bandwidth environments. Lastly, Attah et al. (2024) suggest that regional partnerships and capacity building can be handy for collaborations with local technology firms and research institutions which can support the development of scalable and contextually relevant

analytics tools. These partnerships can help bridge the gap in technical skills and promote the creation of sustainable analytics ecosystems grounded in local expertise and ownership.

Discussion

The findings from this study affirm the increasing relevance and uptake of ML and LA across African HEIs, albeit with significant contextual limitations. As outlined in the reviewed literature (Appendix 1), the application of ML techniques, particularly ensemble methods such as RF, SVM, and DT, has demonstrated substantial promise in areas such as dropout prediction (Dake & Buabeng Andoh, 2022; Asogwa et al., 2023), student performance forecasting (Kitaka, 2023), and risk detection (Elbouknify et al., 2025). These findings align with global trends that underscore the predictive potential of ML in educational contexts (Larusson & White, 2014; Papamitsiou & Economides, 2014). Nonetheless, the African experience with LA diverges from more developed contexts due to infrastructural disparities and limited access to quality datasets, echoing earlier concerns raised by Prinsloo and Slade (2016) and more recently by Williamson and Eynon (2020), who caution against uncritical adoption of Western models of educational data science. While the predictive performance reported by some studies is competitive, e.g., Elbouknify et al. (2025) with RF achieving 88% accuracy, others remain at the proposal stage or rely on limited datasets, illustrating the uneven maturity of analytics implementations across the continent. A notable contribution of African scholarship lies in its multidimensional approach to LA. Studies such as those by Ngary & Twum-Darko (2024) and Ogundaini & Mlitwa (2023) advocate for expanding LA beyond academic performance to include socio-psychological and behavioral factors, aligning with recommendations by Gašević, Dawson, and Siemens (2015) on holistic learner profiling. These perspectives are essential in contexts where academic success is deeply intertwined with socio-economic and emotional factors. The integration of adaptive systems and feedback loops (Abuodha et al., 2024), as well as AI governance frameworks (Maqoqa, 2025), indicates a growing awareness of the ethical, pedagogical, and institutional complexities inherent in deploying LA at scale.

Despite growing adoption, systemic and infrastructural constraints continue to hamper the effective deployment of LA tools in African universities. Consistent with earlier literature (Macfadyen et al., 2014; Rambe & Moeti, 2017), the present findings confirm that issues such as fragmented data systems, limited technical infrastructure, and insufficient funding impede scalable analytics adoption. The technological deficits identified in studies like Mgeni et al. (2024), where mobile LMS adoption was hindered by poor connectivity and device limitations, reflect broader infrastructural disparities that challenge the feasibility of real-time data collection and personalised feedback mechanisms (Mahama, Amankwah-Sarfo & Gyedu, 2024; Ntorukiri, Kirugua & Kirimi, 2022).

Additionally, challenges around data privacy and governance remain a pervasive issue. As Prinsloo and Kaliisa (2022) emphasise, many African HEIs lack formal data protection frameworks, raising concerns about ethical usage, consent, and compliance. Giuffrida and Hall (2023) also highlight the need for robust institutional policies that safeguard student data while enabling meaningful analytics. Without these structures, the risk of misuse and erosion of trust among stakeholders is high, potentially stalling progress in analytics institutionalisation. The skills gap in educational data science is another persistent barrier. Many institutions rely on external consultants due to a shortage of in-house expertise (Corral de Zubielqui et al., 2015; Nwokeji et al., 2019), limiting long-term sustainability and local capacity building. Furthermore, the pedagogical integration of LA remains superficial in many contexts. Studies such as Maluleke (2024) and Simelane & Mnisi (2023) reveal that analytics use is often confined to surface-level indicators like login frequency or forum participation, which may not accurately reflect student engagement or learning depth, a concern echoed by Ahn et al. (2019) and McKenney & Mor (2015), who advocate for deeper pedagogical alignment and educator training.

A critical theme emerging from the findings is the necessity of contextually adapted analytics strategies. Unlike their counterparts in high-income countries, African HEIs operate in socio-technological environments marked by variability in access, digital literacy, and institutional readiness (Pisa et al., 2020). As such, a "one-size-fits-all" model is both ineffective and potentially inequitable (Prinsloo & Slade, 2016). Localised strategies, such as those proposed by Mithun and Roopadarshini (2024), offer promising pathways. Basic descriptive models and mobile-optimised platforms, for instance, can help lower the entry barrier for institutions at the nascent stage of analytics maturity (Slavakis, Giannakis & Mateos, 2014). Evanick (2024) also emphasises that analytics tools must be mobile-first to accommodate African students' predominant use of smartphones for digital learning, particularly in low-bandwidth settings. Another strategy gaining traction is the development of regional partnerships and collaborative ecosystems (Attah et al., 2024). These alliances between HEIs, local tech firms, and government bodies can facilitate resource sharing, technical training, and the development of culturally and pedagogically relevant analytics frameworks. The value of such collaboration is reflected in studies like Ogundaini & Mlitwa (2023), which call for a broader conceptualisation of LA to include student agency, employability outcomes, and inclusive learning environments.

Conclusion, Recommendations and Future Directions

This study has examined the growing application of ML and LA in African HEIs, revealing both promising advancements and persistent challenges. The review of studies from diverse African contexts highlights the increasing relevance of data-driven decision-making in addressing issues such as student dropout, academic risk, and institutional performance. Various ML techniques—particularly ensemble methods like RF and XGBoost demonstrate effective predictive capabilities, with some studies achieving accuracies upwards of 85%. However, the adoption and institutionalisation of analytics in African HEIs remain uneven, constrained by infrastructural, policy, and human capital limitations. Fragmented data systems, lack of analytics expertise, weak data governance structures, and underdeveloped digital infrastructure significantly hinder the scalability and pedagogical integration of LA. Moreover, contextual factors such as limited internet access, variable digital literacy, and cultural diversity necessitate localised strategies tailored to African realities. Despite these barriers, the research affirms that LA has significant potential to transform educational experiences and outcomes in Africa, if grounded in inclusive, context-sensitive, and ethically responsible frameworks. The emerging discourse in African scholarship increasingly calls for holistic, interdisciplinary, and equity-oriented approaches to LA that extend beyond traditional performance metrics to encompass psycho-social, behavioral, and developmental dimensions.

This study recommends that African HEIs should prioritise the development of comprehensive data governance policies that address privacy, consent, security, and responsible data use. Institutions must align with regional and international data protection standards while fostering trust among stakeholders. Collaborative policy development involving educators, students, administrators, and legal experts is essential. There is an urgent need for investment in ICT infrastructure, data integration systems, and analytics platforms. Additionally, institutions should develop internal expertise by training staff in educational data science, analytics interpretation, and pedagogical integration of LA. Professional development programs and partnerships with local tech firms can address the skills gap. Rather than importing complex analytics solutions, HEIs should adopt simplified, mobile-friendly, and scalable models suited to their stage of data maturity. Descriptive analytics, low-complexity predictive tools, and mobile dashboards offer accessible entry points for many institutions. To ensure meaningful adoption, faculty must be involved from the outset. Institutions should provide training and mentorship to help educators interpret analytics dashboards and integrate insights into instructional design. Engaging academic staff increases the relevance and effectiveness of LA tools. Forming regional consortia, involving universities,

government agencies, and technology providers, can help build shared platforms, standardise practices, and amplify research. These partnerships support cost-sharing, promote localised innovation, and enhance sustainability.

The findings also point to several areas where future research is warranted. First, there is a pressing need for longitudinal and large-scale studies that evaluate the long-term efficacy and equity impacts of LA interventions in African contexts. Much of the existing research remains small-scale or exploratory. Second, there is a lack of standardised evaluation frameworks for LA tools, limiting the comparability and generalisability of results across institutions. Moreover, cross-national studies demonstrate the value of comparative analytics in understanding region-specific dynamics, a research avenue that remains underdeveloped. Finally, the potential for integrating affective and behavioral data into LA systems, warrants further exploration. Such holistic models could yield more accurate and equitable learner profiles and support personalised learning pathways aligned with African students' realities.

Disclosures

Conflict of interest

The author declares no competing interests.

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Appendix 1: Summary of Reviewed Studies on ML & LA in African Universities Context

Study	Scope / Country	ML Methods	Outcome / Accuracy	Data Sample	Key Focus
Dake & Buabeng Andoh (2022)	Ghana	RF, SVM, Multilayer Perceptron (MLP), DT	RF: 70.98% (10 fold); 69.74% (5 fold)	University-level, HEIs (n ≈ 500 students)	Predicting dropout rate
Asogwa et al. (2023)	Nigeria	RF, Random Tree, J48	RF: 79.45%; RT: 78.09%	Federal University Lokoja data	Student attrition
Elbouknify et al. (2025)	Morocco	RF, XGBoost, LR	RF: ~88% accuracy; AUC ~87%	Secondary school data, Ministry of Education	At-risk student detection
Wandera et al. (2020)	South Africa & Sierra Leone	RF, XGBoost, SHAP	Interpretive analysis; predictive quality	Cross-national educational data	Comparative analytics
Abuodha et al. (2024)	Kenya	ML for adaptive LMS	Proposed adaptive feedback loops	Proposal-based	Adaptive LMS design
Maqoqa (2025)	South Africa	AI + LA integration	Institutional performance models	Institutional data	AI/LA governance
Ngary & Twum-Darko (2024)	South Africa	ML + big data theoretical	Framework for academic & psycho-socio analytics	Secondary data	Performance enhancement
Ogundaini & Mlitwa (2023)	Sub-Saharan Africa	Literature analysis	LA for skill & economic outcomes	Conference papers	LA beyond performance
Prinsloo & Kaliisa (2022)	Pan Africa	Scoping review	N/A	Policy & legal data	Data privacy in LA
Mtebe & Mwalumbwe (2017)	Tanzania	LA	Contextual insights	Mbeya University Moodle data	LA in African context
Okewu (2017)	Nigeria	LMS data mining	Predictive models not quantified	Private university in Nigeria	LA in African context
Rumble, Broome & Hodson (2019).	Tanzania, Nigeria	Meta-review of RF, ANN, SVM	Highlights lack of large-scale African datasets	Multi-country synthesis	Survey of ML for student dropout
Hassan et al. (2024)	Somaliland	RF, LR, SVM, NB, DT, KNN	RF: 95% accuracy	2022 national survey	Predicting academic risk
Kitaka (2023)	Kenya (Postgrad e-learning)	Hybrid SVM + RF	100% accuracy (hybrid)	Postgrad courses	Performance prediction in e-learning
Mduma et al. (2019)	Tanzania	DT, ANN, DNN, RF	Not specified	Primary education data (Kenya & Tanzania)	ML for early education monitoring
Maluleke (2024)	African HEIs	PRISMA systematic review	N/A	Systematic literature data	LMS–LA adoption correlations; engagement improves performance
Maluleke (2023)	African HEIs	World Conference on Future	N/A	Conference papers & survey data	Identified engagement clusters; LA intervention impact

		Education case insights			
Badaru & Adu (2022)	South African public universities	Thematic review	N/A	Blackboard (46%) & Moodle (34%) usage data	LMS interaction and course facilitation
Chaka & Nkhobo (2019).	South Africa	Login logs + Gephi SNA	N/A	Student login records	Login frequency as proxy for engagement; dashboard usage trends
Simelane & Mnisi (2023)	South Africa	Survey + interviews (n = 116)	90% educators endorse LMS tools	Educator feedback (n = 116)	LMS forums & Collaborate foster student engagement
Mgeni et al. (2024)	Tanzania	Survey on mobile LMS	N/A	SUZA mobile LMS users (n = 240)	Tech barriers: poor connectivity, device compatibility
Ngulube & Ncube (2025)	South Africa	Systematic review of LMS UX	N/A	Multiple UX studies	UX challenges and improvements in LMS