



## Implementing Learning Analytics at Scale in African Open Distance Learning: A Case Study

**\*\*Christine Ofulue<sup>1</sup>**  
[cofulue@noun.edu.ng](mailto:cofulue@noun.edu.ng)

**Paul Prinsloo<sup>2</sup>**  
Professor Extraordinaire,  
University of South Africa  
[Paul14prinsp@outlook.com](mailto:Paul14prinsp@outlook.com)

**\*\*Adewale Adesina<sup>3</sup>**  
[aadesina@noun.edu.ng](mailto:aadesina@noun.edu.ng)

\*\*National Open University of Nigeria

**\*\*Felix K. Olakulehin<sup>4</sup>**  
[folakulehin@noun.edu.ng](mailto:folakulehin@noun.edu.ng)

**\*\*Oluwaseun Oluyide<sup>5</sup>**  
[ooluyide@noun.edu.ng](mailto:ooluyide@noun.edu.ng)

**\*\*Segun Buhari**  
[sbuhari@noun.edu.ng](mailto:sbuhari@noun.edu.ng)

---

*In 2023, the National Open University of Nigeria (NOUN), the largest open and distance learning (ODL) institution in West Africa, with over 120,000 students, embarked on the ethical implementation of Learning Analytics (LA). This article presents insights into factors affecting LA implementation, drawing on a multimethod case-study research design. It comprises (1) focus group interviews with institutional stakeholders in 2023 regarding the collection, analysis, storage and use of student data at NOUN; (2) quantitative data analysis of Learning Management System (LMS) data from three selected courses serving as pilots in the implementation of LA; and (3) focus group interviews with academics from these courses in 2024 to interpret the data and identify necessary interventions. Preliminary findings suggest that the scattered nature of both analogue and digital data leads to duplication, inconsistent access, and missed opportunities for effective student support. Factors such as the availability and diversity of data, legacy systems in pedagogical approaches, and the balancing of flexibility and openness while ensuring the quality and impact of LA's predictive capabilities for student success and/or risk. The study also noted the influence of external factors such as the internet and electricity infrastructure, political stability, socio-economic and socio-cultural factors. This is the first large-scale implementation of LA in an African ODL institution, and the findings*

---

<sup>1</sup>  <https://orcid.org/0000-0003-3452-5238>

<sup>2</sup>  <https://orcid.org/0000-0002-1838-540X>

<sup>3</sup>  <https://orcid.org/0009-0004-4096-2156>

<sup>4</sup>  <https://orcid.org/0000-0002-7266-9972>

<sup>5</sup>  <https://orcid.org/0000-0002-4528-759X>



*provide valuable insights for other (higher) education institutions in similar contexts worldwide. The results underscore the need for context-appropriate approaches to implementing LA.*

**Keywords:** Implementation; Learning Analytics, National Open University of Nigeria, SHEILA

---

## **Practitioner Notes**

### **What is already known about this topic:**

Research on learning analytics (LA) has shown that it can support a range of practices, including providing richer feedback to students, improving curriculum alignment, and enabling early alert systems. Most of this work focuses on how LA can make teaching, assessment, and student support more effective for individual learners. There are, however, relatively few reported cases of LA being implemented across an entire institution, and none that document such initiatives in African higher education. Although several frameworks exist to guide LA adoption, the SHEILA framework is one of the most commonly referenced.

### **What this study contributes:**

This study reports on the practical challenges of implementing LA in a large, open-and-distance education institution in Africa. It shows how broader societal conditions, infrastructural limitations, legacy systems, and existing pedagogical designs shape both what can be implemented and how useful LA becomes in practice. The study also points to early institutional-level benefits, particularly in revealing the limited influence of long-standing pedagogical and assessment practices on student performance.

### **Implications for practice and/or policy:**

After three years of institution-wide implementation, the findings suggest that LA can act as a lens through which institutions critically reflect on their assumptions about pedagogy, assessment, and student support. While much of the LA literature focuses on how analytics can help students modify their learning behaviours, this case study draws attention to a less-discussed outcome: the role of LA in prompting institutional and instructional change to improve student retention and success.

## Introduction

While Learning Analytics (LA) research in residential higher education (HE) comprises a significant, if not the majority of published research into LA, research into the adoption/deployment of LA in open, distance learning (ODL) is an established and integral part of the LA research base (Fynnet al.2022; Prinsloo, 2019, 2023; Siemens, 2019; Wong, 2019). Prinsloo and Kaliisa (2022) report that there was a paucity of research on LA adoption and deployment in African HE, referring to the impact of the varying degrees of digitisation in African HE, the lack of digital and data infrastructures, the existence of legacy analogue systems that often run in parallel with digital systems, and the general lack of digitally published research in African higher education. Since 2022, there has been a noticeable increase in research on LA in Africa. However, as will be discussed in the literature review, much of this research focuses on the outcomes of LA at the course level, or on specific issues related to the teaching of courses. To the best of our knowledge, there is no published research exploring the institution-wide processes of adopting, implementing, and deploying LA within African HE.

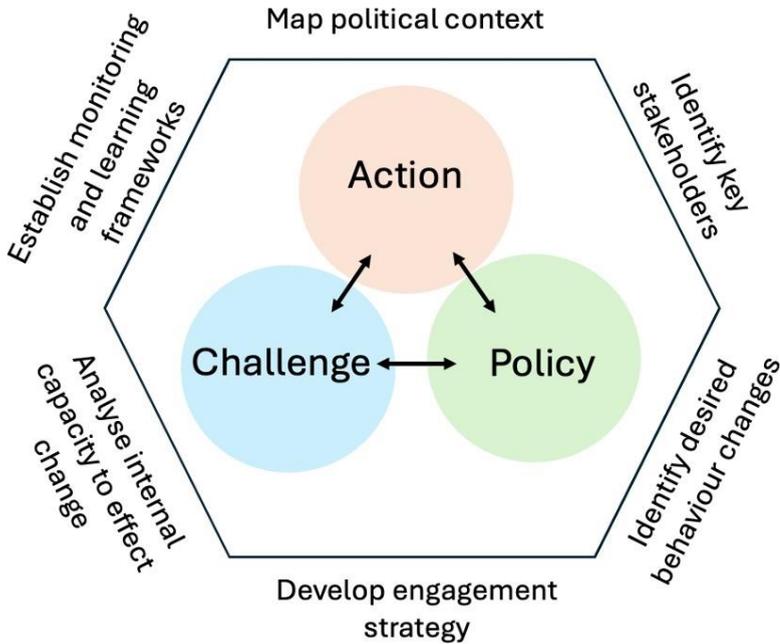
Implementation studies, as a specific research focus, have three purposes, namely 1) to describe the implementation process and discern different process models; 2) to determine and map the various factors that impact the implementation outcomes; and 3) to evaluate the success of such implementation (Nilsen, 2015).

Investigating the implementation process not only makes the different factors impacting the implementation visible, but also maps the influence of key decisions on the interplay between factors, context and outcomes. (Mabert et al., 2003; Leahy et al., 2009). There are also different implementation strategies, of which pilot studies are but one (Burke, 2013). A pilot study allows for testing a new or adjusted part or element of a system, without disrupting the whole system at once.

Research on the different stages of implementation processes includes, but is not limited to, Burke's Four Step Implementation process (2013) or Saldanah's Three Step process (Saldana et al., 2014) or Fixsen,

Blase and Van Dyke's Six Step process (2018) (Also Fixsen, Aijaz, Fixsen, Burks & Schultes, 2021). In the specific context of implementation frameworks and models for LA, Macfadyen (2022) reports on a variety of models and frameworks such as the Learning Analytics Sophistication Model (Siemens et al., 2013), the Learning Analytics Readiness Instrument (LARI) (Arnold, Lonn & Pistilli, 2014) and the Model of Strategic Capability (Colvin et al., 2016). Macfadyen (2022) writes that "... the majority of these models *offer little pragmatic guidance for institutional leaders, and little or no evidence is available in the literature to detail their operationalization, adoption or effectiveness*" (pp. 175- 179; emphasis added). The use of the SHEILA (Supporting Higher Education to Integrate Learning Analytics) model in the implementation of LA (Macfadyen et al., 2014; Tsai et al., 2018) evolved from process models (Colvin et al., 2016; Ferguson et al., 2014) and served as an implementation framework guiding the implementation of LA at NOUN.

The SHEILA framework, originally conceptualised by Tsai et al. (2018), represents a comprehensive approach to learning analytics integration that addresses multiple institutional dimensions. The framework's development highlights the need for a systematic consideration of organisational, technical, and pedagogical factors. For example, Gasevic et al. (2019) emphasise that successful LA implementation cannot rely solely on technological solutions but must incorporate strategic planning that addresses institutional readiness and stakeholder engagement. The core strength of the SHEILA framework lies in its emphasis on stakeholder involvement at every stage of implementation. (See Figure 1 below.) Diverse stakeholder perspectives, particularly those of students and staff, are critical in shaping successful LA initiatives. Multiple stakeholder insights often diverge significantly from institutional assumptions, and this results in inclusive decision-making processes.



**Figure 1:** *The SHEILA framework (Adapted from Tsai et al. 2018, p. 29)*

The implementation of LA at the National Open University of Nigeria (NOUN) started in 2023. This case study provides insights into the early adoption and implementation of LA at NOUN. This single case study aims to answer the following question: *What factors shape the implementation of learning analytics in the service of improving student success at the NOUN?* The rest of the article unfolds as follows: a brief background and overview of NOUN and the LA project, followed by a brief mapping of published evidence of LA in the context of the African continent, specifically Nigeria. This is followed by the research design and methodology, and a presentation of the findings and discussions. The article concludes with selected pointers for implementing LA in low- and middle-income countries, the limitations of the article, and a conclusion.

## **Brief Background of NOUN and the LA Project**

NOUN was established as the first public ODL University in Nigeria and West Africa, currently serving 133,000 active students in 2024. The university has nine faculties: Agricultural Science, Arts, Computing, Education, Health Science, Law, Management Sciences, Science, and Social Sciences. Given the nature of ODL, which emphasises open access and flexibility, student profiles traditionally comprised working adults, and student retention and success remain long-standing concerns (Elibol & Bozkurt, 2023; Kubikova, Bohacova, Slowik & Pavelkova, 2024; Subotzky & Prinsloo, 2011; Olakulehin & Singh, 2013).

In 2022, NOUN initiated the implementation of Learning Analytics (LA) with a multi-stakeholder workshop in 2023 using the SHEILA framework (Macfadyen, 2022; Tsai et al., 2018). This process included (1) mapping the political context; (2) identifying key stakeholders; (3) identifying desired behavioural changes; (4) analysing internal capacity to effect change; and (5) establishing monitoring and learning frameworks. These five steps guided the subsequent development of a Learning Analytics Policy in 2024.

Three courses - Elements of Banking (BNF104), Introduction to Sociology (CSS111) and Elementary Mathematics II (MTH102) - were selected for the pilot implementation in 2024 due to their large enrolments and concerns about student retention, engagement and success. The goal is to gather evidence of a ‘proof of concept’ in these courses as a basis for an institution-wide implementation across all undergraduate courses by the end of 2025. It is important to note that although there is growing evidence of LA research in Africa, dedicated studies on its institutional implementation are still lacking on the continent.

### **LA on the African Continent**

In 2022, Prinsloo and Kaliisa reported that there was very little published evidence about the learning analytics phenomenon in African Higher Education (HE) and no evidence of institution-wide implementations (Prinsloo & Kaliisa, 2022). Against the backdrop of

uneven and generally low levels of access to sustainable and affordable internet provision, low rates in the digitalisation of HE, the immense diversity among the 54 African states' educational systems and publication regimes, and the interchangeable use of terms such as LA and Educational Data Mining, the scoping review by Prinsloo & Kaliisa (2022) reported on 15 studies. The findings of this scoping review, *inter alia*, were that most of the studies in the corpus of analysis were from South Africa, that many of the publications were conceptual and/or theoretical, and that one of the primary foci of the research was ethical considerations.

Since 2022, several scoping and systematic reviews on LA have been conducted on the African continent. While the findings generally indicate growth in LA, it is challenging to obtain a detailed picture because the different reviews used various databases, search strategies, and terms, and included different selections of publication types, such as peer-reviewed articles, chapters, conference proceedings, and books. For example, the systematic review by Maluleke (2024) reports on a corpus of analysis of 143 studies (using Scopus and Google Scholar and reporting on journal articles, conference papers, books, and book chapters), while the systematic review by Ngulube and Ncube (2025) used, as databases, ACM Digital Library, ERIC, Scopus, and Web of Science, a different set of search terms as well as using the Critical Appraisal Skills Programme (CASP) checklist for quality assessment of the different studies including conceptual clarity and comprehensiveness, methodological rigour, sampling clarity and value of the findings. Interestingly, the study also excluded conceptual and theoretical research as well as qualitative studies.

Maluleke (2024) shows exponential growth in research on LA in Africa and, interestingly, provides evidence that the six countries producing the most research on LA (from most to least) are Morocco, South Africa, Nigeria, Ethiopia, Algeria, and Kenya. The review found that "Universities are increasingly using LMS-based LA to make informed decisions at various levels, from institutional to course section" (p. 144) and that the adoption of LA was directly linked to the increasing use of LMS platforms. The review by Ngulube and Ncube (2025) focused on the combination of Learning Analytics (LA) and the

identification of at-risk students, and they found that “administrative data emerged as the most frequently used data source,” combined with student learning behaviour data from the Learning Management System (LMS). More generally, the analysis provided evidence of “the efficacy of early identification in enabling institutions to proactively implement targeted interventions, such as tutoring and academic advising” (p. 127).

### **LA in Nigeria**

Interestingly, while several articles address LA in the Nigerian HE context, none focused on its *institutional implementation*. Additionally, there is a lack of research studies applying LA within specific courses or disciplinary contexts. Many studies, however, have demonstrated the use of Artificial Intelligence (AI)/Machine Learning (ML) in predicting academic success and retention. For example, Ododo et al. (2022) achieved an 85% accuracy in predicting the academic success of a cohort of NOUN students with the Random Forest classifier, while Ndunagu et al. (2024) employed deep learning to analyse the attrition of 2,000 *inactive* NOUN students. These studies demonstrate the potential of algorithmic applications for LA but do not explore real-time implementation and institutional integration. Ezeanya et al. (2024) investigated AI-powered social interaction tools, whilst Ndunagu et al. (2025) and Morgridge et al. (2024) tested chatbot-based support systems at NOUN. Systematic challenges to the potential adoption of LA, though not analysing LA itself, have also been highlighted, such as Internet access barriers (Adamu, 2024) and the importance of online interaction (Aboderin & Laleye, 2019). Furthermore, Ofulue, Adesina et al. (2024) proposed a national ODL research agenda that includes LA, while Prinsloo (2022) emphasised the need for context-specific interventions. Olojede and Olakulehin (2024) called for human-centred approaches to address ethical, legal, and pedagogical challenges. While the potential for LA in Nigeria's higher education is evident, significant gaps in implementation and contextual adaptation remain and should be addressed for meaningful progress.

## Research Questions

The overarching research question guiding this study is: What factors **shape the implementation** of LA in the service of improving student success at the NOUN?

The following sub-research questions also inform the study:

**Sub-RQ 1:** What are the lecturer perceptions regarding factors impacting student success at NOUN that are within the control of students and faculty?

**Sub-RQ 2:** What can be learnt regarding the factors impacting student success at NOUN using student demographic and administrative data?

**Sub-RQ3:** What can be learnt regarding the factors impacting student success at NOUN using student learning behaviour data on the LMS, and course pass rates?

**Sub-RQ 4:** What data does NOUN already have, where is it located, who has access to it, for what purposes and under what conditions?

## Methodology

This study adopted a qualitative, single exploratory case study research design (Yin, 2018), using a differentiated data collection strategy consisting of four separate but linked actions resulting in four ‘snapshots’ (linked to the four sub-research questions. In a very early exposition, Schramm (1971) describes the purpose of case study research as trying “...to illuminate a decision or set of decisions: why they were taken, how they were implemented, and with what result” (p. 6). In reflecting on Schramm’s (1971) description, Yin (2018) defines case study research as investigating “a contemporary phenomenon (the ‘case’) in depth and within its real-world context, especially when the boundaries between phenomenon and context may not be clearly evident” (p. 50). (Also see Brown, 2008; Merriam, 1988). As Yin (2018) and others (e.g. Miles, 2015; Thomas, 2011) indicate, the aim of a case study research design is not to generalise to similar cases but rather to be “generalisable to theoretical propositions and not to populations or universes” (p. 58). The value contribution of this case study is to provide insights into the factors affecting the implementation of LA at NOUN.

In line with Yin's (2018) guidelines for ensuring validity and reliability in case studies, the following **Table 1** provides an overview of the steps taken:

Construct validity	Used multiple sources of data collection - Focus Group Interviews (FGIs), surveys, and quantitative data analysis Shared the analysis of the data during the different phases with participants for verification and input
Internal validity	Transparency in the use of evidence in the findings and discussions Considered rival explanations
External validity	While there are many theories and frameworks for investigating why individuals and institutions adopt technologies, this research aimed to first inductively map the factors and choices and then to link them to a selection of theories
Reliability	The elements of the case study protocol are available in the case study report. A clear chain of evidence

### **Overview of sub-research questions, populations, sampling strategies, methods and methodological norms**

Table 1 provides an overview of the sub-research questions, research design, populations, sampling strategies, methods of analysis and methodological norms. The details of each snapshot are discussed in the section following the table.

**Table 2:** *Overview of questions, populations, sampling strategies, and methods of analysis*

	<b>Snapshot 1</b>	<b>Snapshot 2</b>	<b>Snapshot 3</b>	<b>Snapshot 4</b>
<b>Which sub-RQ?</b>	<b>Sub-RQ 1:</b> What are the lecturer perceptions regarding factors impacting student success at NOUN that are within the control of students and faculty?	<b>Sub-RQ 2:</b> What can be learned regarding the factors impacting student success at NOUN using student demographic and administrative data?	<b>Sub-RQ 3:</b> What can be learned regarding the factors impacting student success at NOUN using student learning behaviour data on the LMS, and course pass rates?	<b>Sub-RQ 4:</b> What data does NOUN already have, where is it located, who has access to it, for what purposes and under what conditions?
<b>Research design</b>	Qualitative analysis - frequency tables combined with observations	Quantitative analysis using a Two-way table and chi-square of demography and CHAID analysis.	Quantitative - descriptive statistics	FGIs: Qualitative analysis

	<b>Snapshot 1</b>	<b>Snapshot 2</b>	<b>Snapshot 3</b>	<b>Snapshot 4</b>
<b>Data collection methodology</b>	FGIs combined with a qualitative survey.	Student administrative and course success data.	Analysis of Tutor Marked Assignment (TMA) scores in relation to pass scores and synchronous online facilitation sessions.	FGIs plus observational data
<b>Population/sampling strategy</b>	Departmental staff responsible for the three pilot courses / Purposeful sampling.	The three pilot courses and data from the student administration system, and course success rates.	LMS data of all registered students in the three pilot courses - log and attendance data.	Of the about 20 directorates at NOUN, 7 were purposefully selected because they were involved as producers or users of student data.
<b>Method of analysis</b>	Deductive analysis of qualitative survey used during FGIs, frequency analysis	Quantitative analysis using a Two-way table and chi-square of demography and CHAID analysis.	Quantitative data analysis - descriptive statistics.	Deductive analysis of the qualitative survey used during the FGIs

	<b>Snapshot 1</b>	<b>Snapshot 2</b>	<b>Snapshot 3</b>	<b>Snapshot 4</b>
<b>Methodological norms</b>	Triangulation, verifying accounts with participants, creating an audit trail, Critical peer debriefing and checking (Bos & Tarnai, 1999; Creswell, 2007; Lincoln & Guba, 1985)	See the full discussion in the text	Content, criterion and construct validity (Rourke & Anderson, 2004).	Verifying accounts with participants, creating an audit trail. Critical peer checking (Bos & Tarnai, 1999; Creswell, 2007; Lincoln & Guba, 1985)

**Snapshot 1 - Focus Group Interviews: Background, design, population and sampling (inclusion criteria and realised sample and method of data analysis (Overview)**

In September 2024, three FGIs were held with full-time lecturers from the departments hosting the three different pilot courses. The invitation to participate was sent to the Heads of departments, and inclusion criteria prioritised staff directly involved with the courses, such as Heads of Departments, Examination officers, and Course Coordinators. Administrative staff were not included in the study. Participation was voluntary and based on availability.

The population for the FGIs comprised 26 full-time lecturers across three departments with 12 attending the FGIs as shown in the following breakdown in Table 2 below:

**Table 3:** *An overview of the populations and realised sample*

<b>Department</b>	<b>Populations (Teaching staff)</b>	<b>Sample (Attended)</b>
Criminology and Security Studies	9	6
Financial Studies	10	4
Mathematics	7	2

During the FGIs, participants completed a qualitative questionnaire with open-ended questions and quantitative elements using Likert-type items. This questionnaire was based on the proposed socio-critical framework for student success by Subotzky and Prinsloo (2011) and focused on several key areas:

- Macro-societal factors affecting student success (e.g. political, social, economic, legal, environmental and technological).
- Learner habitus encompasses the past and current immediate context, learning experiences and characteristics and attitudes
- Student readiness/preparedness
- Students' learning behaviour during the course
- Macro-societal factors affecting lecturers' teaching
- Pedagogical and assessment choices made by lecturers
- Various types of student support (cognitive, administrative and psycho-social)

Lecturers were also requested to identify and rank at least three institutional factors affecting their teaching, and to specify the student data they wish to access to enhance their teaching effectiveness and student support.

Following the completion of the questionnaire, the findings from the analysis of sub-research question 3 (Snapshot 3) were shared with the Focus Group and discussed in conjunction with their responses.

## **Snapshot 2: Quantitative analysis of Demographics and Course Outcomes.**

This analysis aimed to explore relationships between student demographic characteristics and course outcomes across the three pilot courses. The goal was to identify patterns that could inform early identification of students at risk and guide targeted intervention.

### **Population and Data Sources**

The dataset comprised 14,752 records extracted from NOUN's student information system for registered students in the three pilot courses (BFN104, CSS111, and MTH102) during the 2023 academic year. Demographic variables included gender, age, marital status, and geopolitical zone, while course outcomes data were categorised as 'Passed (OK)' or 'Carry-over' (failed) based on final grades.

### **Method of Analysis**

Two-way Contingency Tables and Chi-Square Analysis. Bivariate relationships between demographic variables and course outcomes were examined through two-way tables. Chi-square tests of independence assessed if observed associations were statistically significant. Pass/fail ratios quantified differences between groups.

CHAID (Chi-square Automatic Interaction Detection) Analysis. This method was employed to identify hierarchical relationships and interaction effects between demographic predictors and course outcomes (Kass, 1980). By recursively partitioning the dataset based on significant chi-square associations, CHAID revealed the combinations of demographic factors that predict student success or failure. The analysis produces an interpretable tree structure showing the most influential variables and their interactions in predicting course outcomes (Hair et al., 2010). All major decision tree splits were highly statistically significant, indicating strong predictive relationships.

### **Methodological Norms**

*Content validity* involved using standardised university registration data (Creswell, 2007). *Construct and criterion validity* were ensured through commonly used demographic variables validated in previous

studies of student success predictors (Subotzky and Prinsloo, 2011) and actual course outcomes from official institutional records, respectively.

*Data reliability* was enhanced using administrative records, thereby minimising bias (Creswell, 2007). Cross-validation in the CHAID analysis ensured model stability (Hair et al., 2010).

**Generalisability:** *Internal validity* was strengthened by the large sample size (n=14,752) spanning multiple courses (Field, 2013). However, *external validity* is limited to the specific context of NOUN and similar ODL institutions in comparable socio-economic environments. The findings are not generalisable to residential universities in significantly different infrastructural or cultural contexts.

### **Analytical Assumptions and Limitations**

The chi-square analysis assumed independence of observations (Field, 2013) and missing demographic data were handled through listwise deletion. CHAID's recursive approach may lead to unstable trees when sample sizes in terminal nodes become too small (Kass, 1980). Both methods can identify associations but cannot infer causation. The analysis also assumes that demographic categories adequately capture relevant student characteristics, potentially overlooking unmeasured variables that influence academic performance in the ODL context.

### **Data Quality Assurance**

Data quality was assured through data cleaning protocols, including demographic verification, outlier identification, and independent coder validation, and the findings were triangulated (Snapshots 1 and 3), enhancing the overall interpretive value and providing a more comprehensive understanding of factors influencing student success at NOUN (Lincoln & Guba, 1985).

### **Snapshot 3 - Quantitative analysis: Student Formative Assessment Data and Engagement Metrics**

This analysis examines possible correlations among student FA data, attendance at synchronous online sessions, and final course grades. The goal was to develop student success and risk profiles while identifying

trends in course pass rates relative to pedagogical design factors. Data were collected from the LMS detailing the number of students who participated in live sessions and those who accessed recorded sessions of the courses for the 2023 semester. Reports and log files were used to compile this information.

#### **Snapshot 4 - Focus Group Interviews - Data audit**

As reported by Ofulue, Opataye, et al. (2024), a data audit involving 7 out of about 20 directorates at NOUN provided critical insights into institutional data management practices. The participating directorates—Learner Support Services (LSS), Course Material Development Unit (CMDU), Quality Assurance, Examinations and Assessment, Advancement and Linkages, Management and Information Systems (MIS), and Learning Content Management Systems (LCMS)—were purposively selected for their role as primary data-*generating* units. Other directorates that utilise secondary data were excluded from the FGIs. Notably, faculties were excluded since their data were primarily sourced from MIS and LCMS, and the Student Accounts Unit did not participate, as relevant information was obtained from LSS to inform the research.

Ofulue, Opataye, et al. (2024) noted that published research on LA often overlooked the importance of conducting a data audit to understand an institution's data landscape. For example, the widely used SHEILA framework for LA implementation did not mention a data audit as an essential initial step (Tsai et al., 2018). A data audit is vital for assessing data quality, utility, and governance, facilitating efficiency, risk management, and informed data access (Jones, Ball, & Ekmekcioglu, 2008). By identifying data ownership and curation practices, institutions can prioritise resources and mitigate risks effectively. For LA to succeed, access to meaningful and valuable data is paramount. Collecting data is one thing; using it effectively for pedagogical purposes is another (Schlappy, 2016).

The purpose of this data audit was to evaluate the available data, address existing gaps and identify any missing elements. Central questions guiding the process included: What data do we need? What

data exists? What is its description? These questions framed our discussions with representatives from the relevant directorates.

The FGIs were structured around a protocol that ensured a logical progression of questions, facilitating in-depth exploration of each topic. The ten questions posed focused on the nature and format of the data, ownership, usage, hosting, access rights, and sharing conditions. Responses were recorded and organised in tabular format, accompanied by field notes for enriched insights. After each session, researchers collaborated to refine the theme and examine departmental perspectives, deepening our understanding of how this data could support the broader LA initiatives at NOUN. For further details and context, see Ofulue, Opatye, et al. (2024).

## **Analysis and Findings**

### **Sub-RQ1: What are the lecturer perceptions regarding factors impacting student success at NOUN that are within the control of students and faculty? (Snapshot 1)**

This analysis is based on a small sample of participants (n=11), comprising heads of departments and course coordinators from three pilot courses. While the findings cannot be generalised across all academic staff, they offer valuable insights into the perceptions of those directly responsible for teaching and supporting these courses (Subotzky & Prinsloo, 2011).

The lecturers' understanding of factors affecting students' learning is reflected in their empathy towards students' concerns and awareness of the external challenges students face. At NOUN, where students are spread across diverse regions of Nigeria, various infrastructure issues—such as inconsistent electricity supply and differing access to digital tools—along with cultural and language barriers complicate students' performance beyond mere commitment.<sup>1</sup>

---

<sup>1</sup> Note: For reporting purposes, the paper refers to 'agreed' and 'disagreed' as including 'strongly agreed' and 'strongly disagreed' unless there is an interesting variation in the percentages.

Regarding survey responses, 92% of participants acknowledged the impact of macro-societal factors (e.g., strikes, regulatory changes, national internet infrastructure) on students' learning, with 50% strongly agreeing. Socioeconomic status (91%) and family responsibilities (92%) were also seen as significant contributors to student success. However, only 34% recognised cultural factors as having an impact. A noteworthy 92% agreed that students' readiness for online learning was essential for success, and 92% also noted the importance of readiness concerning specific modules, albeit with only 42% strongly agreeing. Interestingly, just 50% believed that taking on too many courses negatively affects student success, and 17% disagreed that participating in synchronous sessions significantly contributes to success.

### **Sub-RQ 2: What can be learnt regarding the factors impacting student success at NOUN using student demographic and administrative data? (Snapshot 2)**

#### **Findings from the Two-way table and Chi-square test**

The analysis included data from 14,752 students across the three courses, comprising 8,204 males and 6,548 females, yielding a gender ratio of 1.25.

The comparison of the pass/fail ratio of gender, age, marital status and geopolitical zone resulted in the following:

**Gender:** Female students exhibited a significantly better pass/fail ratio (5.11) compared to male students (3.79). However, in one course, male students had a higher, though not statistically significant, ratio of 5.72 versus 5.30, indicating variability in performance.

**Age:** Age trends revealed inconsistencies in pass/fail ratios across courses. Younger students outperformed their older peers in MTH 102 (2.46 vs. 2.34). In contrast, in CSS 111 and BFN 104, older students demonstrated better performance, suggesting a potential age-related advantage in some disciplines, particularly those where professional qualifications are pursued.

**Marital status:** In MTH 102, single students had a higher pass/fail ratio (2.36) than their married counterparts (2.01), whereas in CSS 111, the difference was not statistically significant. In BFN 104, married students showed a better ratio (5.11) than singles (7.76). This indicates that marital status does not consistently impact performance across all courses.

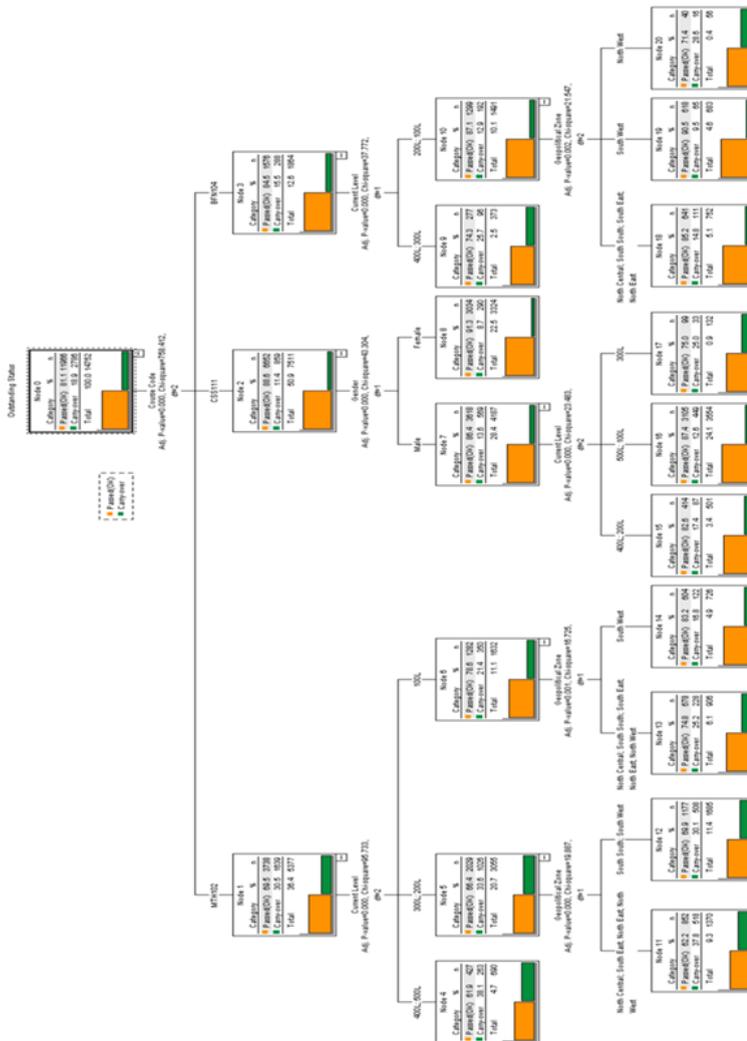
**Geopolitical Zones:** In terms of the relationship between geopolitical zones and student success, the pass/fail ratio was significantly higher for Southern students than for their Northern counterparts. The ratio was 4.54 vs 4.01 for the Southern and Northern students, respectively. Students from the Southern part of the country proved most likely to outperform their Northern counterparts. Further exploration into the impact of geographical differences on student outcomes is warranted to fully understand the broader implications for teaching and learning at NOUN.

In terms of *actionable* insights, although interesting, the findings from the two-way table and Chi-square test provide a basis for interventions, such as examining student support structures in the northern part of Nigeria, as well as further research on student registrations in elective courses.

### **Findings from the CHAID Decision Tree**

The CHAID decision tree has two target variable categories: Passed (OK) and Carry-over. The tree shows the interacting factors that predict whether a student “Passed (OK)” or had a “Carry-Over”. This CHAID tree provides a clear hierarchical understanding of how these factors interact to predict the "Passed (OK)" or "Carry-over" outcome. It highlights the key segments of the population with different probabilities of success by region, age, gender, and geographic distribution.

The Root Node (Node 0) shows the overall distribution representing the entire dataset of 14,752 students. We can see the overall proportion of “Passed (Ok) (81.1%) and “Carry-Over” (18.9%) across all observations. (See Figure 2 below).



**Figure 2: An overview of the CHAID analysis**

The following are key takeaways from the CHAID analysis.

1. The selected course codes are the most important influencing outcome; MTH 102 stands out with a significantly lower "Passed (OK)" rate.
2. Within the combined "North Central, South-South, Northwest, Southeast" geopolitical zones, age plays a vital role, with those aged 40+ and 20-29 performing better than the 30-39 age group.

3. In the Southwest, gender is a significant differentiator, with females achieving a higher "Passed (OK)" rate than males.
4. For males in CSS 111, within specific geopolitical zones, outcomes are further differentiated.

### **Sub-RQ 3: What can be learnt regarding the factors impacting student success at NOUN using student learning behaviour data on the LMS and course pass rates? (Snapshot 3)**

This article focuses on findings related to student behaviour data and course pass rates. It highlights the correlation between students' TMA scores, examination scores, and moderated scores across pilot courses.

Key observations include:

In BNF104 First Semester 2024:

- Of the 129 students who failed the course, 85 (66%) had high TMA scores.
- Of the 66 students who did not write the examinations, 49 students (74%) had high TMA scores.

In MTH102 First Semester 2024:

- 39% of students had high FA scores but below-average Examination scores and failed the course.
- Of the 31% of students who failed the course, 210 did not write the exam, and among these 210, 65% had high FA scores.

In CSS111 First Semester 2024:

- The pass rate for the course was very high (88%), but among those who failed, 43% had high FA scores.

Regarding online engagement, observations reveal:

- Students primarily interacted by viewing quizzes and submitting FAs.
- The Discussion Forum was underutilised.
- Attendance in synchronous sessions was minimal, and even fewer students accessed recorded sessions.

Summary insights from the descriptive analysis include the following:

- High FA scores are not a predictor for course pass, as previously suspected.
- Students with high FAs are at risk of failing or not sitting for the exam and should receive an alert/student counselling intervention.
- Repeaters in key courses like BFN and MTH are a high-risk category and should receive an alert/student counselling intervention.

**Sub-RQ 4: What data does NOUN already have, where is it located, who has access to it, for what purposes and under what conditions? (Snapshot 4)**

The FGIs with the seven (7) directorates provided detailed insights into data governance, access, and usage. The field notes highlight the challenges in obtaining data and varying procedures across directorates.<sup>2</sup>

The analysis identified a wealth of data comprising admissions, registration, LMS usage, student visits to regional centres, access to Counselling services, and assessment and examination administration. However, this data is currently fragmented across the institution, with some in analogue format and most digitised. Many directorates were unaware of the data available within their reach, leading to challenges in duplicating data collection and data-driven decision-making. This oversight underscores the need for improved data accessibility and collaboration among directorates to leverage existing resources effectively.

What became evident during these FGIs was the lack of seamless access to and integration of stored data. The data audit illustrated not only an urgent need for a comprehensive, institution-wide analysis of current and future data needs to inform pedagogy and support, but also the need for a data process analysis to determine current and future data-push and data-pull demands. There is potential to aggregate data and automate access through the institutional data centre and

---

<sup>2</sup> Note: For reporting purposes, the paper refers to 'agreed' and 'disagreed' as including 'strongly agreed' and 'strongly disagreed' unless there is an interesting variation in the percentages.

dashboards, enabling differentiated access for students, course administrators, faculty, and student support services, including counselling and regional centres.

The interviews underscored the need for a consistent approach to data governance, specifically regarding collection, access and the purposes for which data is used. The value of data - both existing and required - was not fully realised. Interestingly, students were primarily seen as data producers rather than data users, highlighting an urgent need to democratise ethical access to this data.

## **Discussions**

The implementation of LA at NOUN relied on the SHEILA framework, which involved mapping the political context, identifying key stakeholders, and determining desired behavioural changes alongside a 2022-2023 engagement strategy. Critical to this initiative was the development of a Learning Analytics Policy that outlines the principles for implementing LA and provides guidance on initial steps.

The four snapshots reported in this article were instrumental in assessing the institution's understanding of student success (Snapshot 1) and mapping the institution's data landscape (Snapshot 4). While these snapshots provided valuable insights, they revealed a gap between the anticipated benefits of LA and the actual actionable data currently accessible to the institution, especially evident in three pilot courses. Notably, the data revealed that understanding student success extends beyond mere demographic information.

Snapshot 2, which employed a two-way table, the Chi-square test, and CHAID analysis, did not yield immediate, enlightening results. It failed to create comprehensive profiles that linked student success or identified at-risk students despite hinting at areas for further exploration, such as the implications of electives and the differing support needs of single versus married students.

Snapshot 3, however, uncovered a noteworthy lack of correlation between TMA scores and final course outcomes. This finding was both

significant and uncomfortable, highlighting that at NOUN, the current structure of TMAs and pedagogical practices might not effectively prepare students for examinations.

Furthermore, low attendance at synchronous online facilitation sessions—critical for fostering engagement in a distance-learning context—emerged as a concern.

Many students also did not utilise recordings of these sessions, undermining NOUN's commitment to enhancing interaction and collaborative learning.

The third significant finding, as presented in Snapshot 4, relates to the outcomes of the data audit. Discussions involving the FGIs revealed these insights, prompting the senior management team at NOUN to recognise the prevailing challenges and the opportunities for enhancing Learning Analytics. This recognition is essential for advancing data-driven strategies that effectively support student success and inform institutional practices.

Since the findings were discussed during the FGIs reported on in Snapshot 1 and during discussions with the senior Management team, NOUN established a Data centre to address the findings and significantly shape the implementation of LA.

## **Limitations**

This overview presents four interconnected snapshots of the implementation of Learning Analytics (LA) and the insights they offer regarding implementation and future steps. While we acknowledge that this approach sacrifices an in-depth discussion of each snapshot, our focus was on the broader implications and insights gained from these snapshots rather than their standalone value.

## Conclusion

The findings from this study highlight both the potential for Learning Analytics (LA) at the National Open University of Nigeria (NOUN) and the challenges that remain.

While opportunities exist, it is essential to cultivate a culture that values data accessibility and governance to enhance the educational experience. Although the outcomes of this single-case study cannot be generalised to all low- and middle-income countries, they offer valuable insights into LA implementation.

The analysis of four sub-research questions—presented as distinct snapshots—reveals critical factors influencing the success of LA in this large African distance education institution. Using the SHEILA framework as a guide, we explored how data-informed decision-making can transform pedagogy, assessment, and broader understandings of openness and responsibility.

Although still in its infancy, the implementation of LA at NOUN illustrates a promising pathway toward addressing educational disparities and meeting the needs of a diverse student population, particularly those who have historically faced barriers to higher education. Through thoughtful application, LA can contribute to a more equitable and flexible educational environment.

## Postscript

Since the findings of this study, several activities have been initiated at NOUN. These include a reflective examination of the pedagogical conditions that currently limit the effectiveness of learning analytics in practice, particularly the challenge of making students' learning visible in highly flexible, open, and distance learning models. Lessons learned from this work will be reported at LAK26. In addition, a redesign of the pilot courses is underway to support the adoption of data-informed, process-led pedagogical approaches that increase engagement and make learning visible. Collectively, these activities are intended to

enable NOUN to realise the full potential of learning analytics in supporting student success.

### **Acknowledgement**

The authors acknowledge that an earlier preliminary analysis of the Snapshot 4 (Data audit) data was presented at LAK'24 as a Practitioner Paper (Ofulue, Opataye, et al., 2024), and a preliminary overview of the initial analysis of the different snapshots was presented at the PCF'11 conference held in Gaborone, Botswana.

## References

- Abaa, A. (2025). Personalised learning paths in open education systems. *NIU Journal of Educational Research*, 11(1), 21–29. <https://doi:10.58709/niujed.v11i1.2124>
- Aboderin, O. S., & Laleye, A. (2019). The Relationship between Online Interaction and Academic Performance of Distance E-Learners in a Nigerian University. *American International Journal of Education and Linguistics Research*, 2(1), 25–33. <https://doi.org/10.46545/aijelr.v2i1.72>
- Adamu, D. C. (2024). An evaluation of the experience and challenges faced in online learning by undergraduate students at the National Open University of Nigeria. *E-Journal of Humanities, Arts and Social Sciences*, 2099–2112. <https://doi.org/10.38159/ehass.20245137>
- Arnold, K.E., Lonn, S.& Pistilli, M.D. (2014). An Exercise in Institutional Reflection: The Learning Analytics Readiness Instrument (LARI). In: Fourth International Conference on Learning Analytics & Knowledge, March 2014. Indianapolis, IN, USA: New York, USA: ACM, 2014, pp. 163– 167. DOI: 10.1145 / 2567574.2567621.
- Bos, W. & Tarnai, C. (1999). Content analysis in empirical social research, *International Journal of Educational Research*, 31, 659—671.
- British Educational Research Association (BERA). (2024). Ethical Guidelines for Educational Research. [Fifth edition]. Retrieved from <https://www.bera.ac.uk/publication/ethical-guidelines-for-educational-research-fifth-edition-2024>
- Burke, R., (2013). *Project Management: Planning and Control Techniques*. Fifth ed. Chichester, West Sussex: John Wiley and Sons Ltd.
- Clark, J. A. (2023). Learning Analytics Implementations in Australian Universities: Towards a Model of Success. Retrieved from <https://research-repository.griffith.edu.au/items/e867899d-f2bb-42bf-b426-8d672bdbc295>

- Colvin, C., Rogers, T., Dawson, S., Gasevic, D., Buckingham Shum, S.K. Alexander, N.S., Lockyer, L., Kennedy, G., Corrin, L., & Fisher, J. (2016). Student Retention and Learning Analytics: A Snapshot of Australian Practices and a Framework for Advancement. Canberra, ACT: Australian Government Office for Learning and Teaching. Retrieved from <http://hdl.handle.net/10453/117173>
- Creswell, J.W. (2007). *Qualitative inquiry & research design. Choosing among five approaches, 2nd edition*, London, UK: SAGE Publications.
- Ezeanya, C. U., Ukaigwe, J. A., Ogbaga, I. N., & Kwanashie, A. (2024). Enhancing Social Engagement among Online Learners Using AI-Driven Tools: National Open University of Nigeria Learners' Perspective. *ABUAD Journal of Engineering Research and Development (AJERD)*, 7(2), 78–85.
- Ferguson, R., Clow, D., Macfadyen, L., Essa, A., Dawson, S., & Alexander, S. (2014). Setting Learning Analytics in Context: Overcoming the Barriers to Large-Scale Adoption. *Journal of Learning Analytics* 1(3), pp. 120–144.
- Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). Sage Publications.
- Fixsen, A. A., Aijaz, M., Fixsen, D. L., Burks, E., & Schultes, M. T. (2021). Implementation frameworks: An analysis. *Chapel Hill, NC: Active Implementation Research Network*.
- Fixsen, D., Blase, K., & Van Dyke, M. (2018). Assessing implementation stages. Retrieved from Chapel Hill, NC: Active Implementation Research Network: [www.activeimplementation.org/resources](http://www.activeimplementation.org/resources).
- Fynn, A., Adamiak, J., & Young, K. (2022). A Global South perspective on learning analytics in an open distance e-learning (ODeL) institution. In Prinsloo, P., Slade, S. & Khalil, M. (eds.), *Learning Analytics in Open and Distributed Learning: Potential and Challenges* (pp. 31-45). Singapore: Springer Nature Singapore.

- Garcia, S., Marques, E., Mello, R. F., Gašević, D., Rodrigues, R. L., & Falcão, T. P. (2021). Adopting learning analytics in a Brazilian higher education institution: Ideal and predicted expectations. In *Latin American Conference on Learning Analytics, LALA 2021* (pp. 8–17). Universidad Católica de Santa María.
- Gašević, D., Tsai, Y. S., & Drachsler, H. (2022). Learning analytics in higher education—Stakeholders, strategy and scale. *The internet and higher education*, 52, 100833.
- Gašević, D., Tsai, Y. S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology*, 36(4), 342–353.
- Gray, G., Schalk, A. E., Cooke, G., Murnion, P., Rooney, P., & O'Rourke, K. C. (2022). Stakeholders' insights on learning analytics: Perspectives of students and staff. *Computers & Education*, 187, 104550.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.
- Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. *Applied Statistics*, 29(2), 119–127.
- Kekez, I., & Šimić, D. (2023). Learning Analytics Frameworks: A Review of Challenges and Practices in Higher Education. In *34th Central European Conference on Information and Intelligent Systems (CECIIS 2023)* (pp. 231- 238).
- Leahy, M.J., Thielsen, V.A., Millington, M.J., Austin, B., & Fleming, A. (2009). Quality assurance and program evaluation: Terms, models, and applications. *Journal of Rehabilitation Administration*, 33(2), 69–82.
- Lin, J., Harada, K., & Goto, H. (2023). Frameworks of Designing and Implementing Learning Analytics in Educational Institutions: A Review. Available at SSRN 4558855.
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage Publications. Lincoln, Y. S., & Guba, E. G. (1990). Judging the

- quality of case study reports. *International Journal of Qualitative Studies in Education*, 3(1), 53–59. DOI:10.1080/0951839900030105
- Mabert, V., Soni, A. & Venkataramanan, M. (2003). Enterprise resource planning: Managing the implementation process, *European Journal of Operational Research*, 146(2), 302–314. doi: [http://dx.doi.org/10.1016/S0377-2217\(02\)00551-9](http://dx.doi.org/10.1016/S0377-2217(02)00551-9).
- Macfadyen, L. P. (2022). Institutional implementation of learning analytics: current state, Challenges, and guiding frameworks. *The handbook of learning analytics*, 2, 173–186.
- Macfadyen, L. P. (2022). Institutional implementation of learning analytics: current state, Challenges, and guiding frameworks. *The handbook of learning analytics*, 2, 173–186.
- Macfadyen, L.P., Dawson, S., Pardo, A., & Gasevic, D. (2014). Embracing Big Data in Complex Educational Systems: The Learning Analytics Imperative and the Policy Challenge. *Research & Practice in Assessment* 9, pp. 17–28.
- Maluleke, A. F. (2024). Enhancing Learning Analytics through Learning Management Systems Engagement in African Higher Education. *Journal of Education and Learning Technology (JELT)*, 5(6), 130–149.
- Márquez, L., Henríquez, V., Chevreux, H., Scheihing, E., & Guerra, J. (2024).
- Adoption of learning analytics in higher education institutions: A systematic literature review. *British Journal of Educational Technology*, 55(2), 439-459.
- Morgridge, O., Balogun, N. A., & Ndunagu, J. N. Enhancing NOUN Students' Online Learning Experience with an FAQ Chatbot. Available at SSRN 4697903.
- Ndunagu, J. N., Ezeanya, C. U., Onuorah, B. O., Onyeakazi, J. C., & Ukwandu, E. (2025). A Chatbot Student Support System in Open and Distance Learning Institutions. *Computers* 2025, 14, 96. Integration.

- Ndunagu, J. N., Oyewola, D. O., Garki, F. S., Onyeakazi, J. C., Ezeanya, C. U., & Ukwandu, E. (2024). Deep Learning for Predicting Attrition Rate in Open and Distance Learning (ODL) Institutions. *Computers, 13*(9), 229.
- Ngulube, P., & Ncube, M. M. (2025). Leveraging Learning Analytics to Improve the User Experience of Learning Management Systems in Higher Education Institutions. *Information, 16*(5), 419.
- Nilsen, P. (2015). Making sense of implementation theories, models and frameworks, *Implementation Science, 10*(53), 1–13. Doi: 10.1186/s13012-015-0242-0.
- Ododo, E. P., Essien, N. P., & Billy, D. (2022). Modelling and Predicting the Academic Achievement Success of National Open University of Nigeria Students Using Machine Learning Classification Algorithms. *Asia-Africa Journal of Recent Scientific Research, 2*, 120–135.
- Ofulue, C., Adesina, A., Olakulehin, F. K., & Oluyide, O. P. (2024). Implementing learning analytics in data-poor contexts: The role of an institutional data audit. In Proceedings of the Fourteenth International Conference on Learning Analytics & Knowledge (pp. 45–48). Association for Computing Machinery. [https://www.solaresearch.org/wp-content/uploads/2024/03/LAK24\\_CompanionProceedings.pdf](https://www.solaresearch.org/wp-content/uploads/2024/03/LAK24_CompanionProceedings.pdf)
- Ofulue, C., Opataye, J., Awolumate, S., Olakulehin, F. K., Adesina, A., Yabo, A. M., Ugoala, B., Oluyide, O., & Ojedeji, S. (2024). Developing a Research Agenda for Resilient Systems and Innovative Practices in ODeL: Findings from a National Study. *Journal of Learning for Development, 11*(2), 323–348. <https://doi.org/10.56059/jl4d.v11i2.1045>
- Ogunlade, B. O. (2025). Artificial Intelligence-Powered Personalised Learning Paths in Educational System in Nigeria. In P. A. Okebukola (Ed.), *AI and Curriculum Development for the Future* (Vol. 2, pp. 105–116). Sterling Publishers, Slough UK and Delhi, India. <https://eprints.gouni.edu.ng/4428/1/Volume%202->

AI%20and%20Quality%20Higher%20Education%20Handbo  
ok- January%202025.pdf#page=122

- Olojede, H. T., & Olakulehin, F. K. (2024). Africa Dreams of Artificial Intelligence: A Critical Analysis of its Limits in Open and Distance Learning. *Journal of Ethics in Higher Education*, (5), 159–181.
- Prinsloo, P. (2019). Tracking (un)belonging: At the intersections of human-algorithmic student support. The Ninth Pan-Commonwealth Forum (PCF9), 9-12 September 2019, Edinburgh, Scotland. Retrieved from <https://oasis.col.org/entities/publication/1ee094cc-a2fe-471c-9470-8a91685172c9>
- Prinsloo, P. (2022). Improving student retention and success: Realising the (im)possible. *West African Journal of Open and Flexible Learning*, 11(1), 127–134.
- Prinsloo, P. (2023). Learning analytics in open, distance, and digital education (ODDE). In O. Zawacki-Richter & I. Jung (Eds.), *Handbook of open, distance and digital education* (pp. 1021–1036). Springer Nature Singapore.
- Prinsloo, P., & Kaliisa, R. (2022). Learning analytics on the African continent: An emerging research focus and practice. *Journal of Learning Analytics*, 9(2), 218–235.
- Rourke, L., & Anderson, T. (2004). Validity in quantitative content analysis. *Educational technology research and development*, 52(1), 5–18.
- Saldana, L., Chamberlain, P., Bradford, W.D., Campbell, M. & Landsverk, J. (2014). The cost of implementing new strategies (COINS): a method for mapping implementation resources using the stages of implementation completion. *Children and Youth Services Review*, 39, 177–182. DOI 10.1016/j.childyouth.2013.10.006.
- Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, 57(10), 1380–1400.

- Siemens, G. (2019). Learning analytics and open, flexible, and distance learning. *Distance Education*, 40(3), 414–418.
- Siemens, G., Dawson, S., & Lynch, G. (2013). Improving the Quality and Productivity of the Higher Education Sector. Policy and Strategy for Systems-Level Deployment of Learning Analytics. Retrieved from [https://solaresearch.org/wp-content/uploads/2017/06/SoLAR\\_Report\\_2014.pdf](https://solaresearch.org/wp-content/uploads/2017/06/SoLAR_Report_2014.pdf)
- Subotzky, G., & Prinsloo, P. (2011). Turning the tide: A socio-critical model and framework for improving student success in open distance learning at the University of South Africa. *Distance Education*, 32(2), 177–193.
- Tsai, Y. S., Gasevic, D., Whitelock-Wainwright, A., Muñoz-Merino, P. J., Moreno-Marcos, P. M., Fernández, A. R., ... & Benke-Åberg, R. (2018). SHEILA: Supporting Higher Education to Integrate Learning Analytics Research Report.
- Williamson, B. (2025). Re-infrastructuring higher education. *Dialogues on Digital Society*, 1(1), 41–46.
- Williamson, B., Macgilchrist, F., & Potter, J. (2021). Covid-19 controversies and critical research in digital education. *Learning, Media and Technology*, 46(2), 117–127.