International Journal of
Humanities, Education, and Social Sciences

e-ISSN : 3026-0892
p-ISSN : 3026-1422
Index: Harvard, Boston, Sydney, Dimensions, Lens, Scilit, Semantic, Google, etc

https://doi.org/10.58578/IJHESS.v3i3.7291

Awareness and Preparedness for Predictive Analytics: A Case Study of Universities in North-Central Nigeria

Dorcas Sola Daramola[1], Jumoke Oladele[2], Moruf O. Aileru[3]
[1,3]University of Ilorin, Nigeria; [2]University of Johannesburg, South Africa
olatunji.d@unilorin.edu.ng; jumokeo@uj.ac.za

Article Info:

Submitted:	Revised:	Accepted:	Published:
Aug 11, 2025	Sep 4, 2025	Sep 16, 2025	Sep 21, 2025

Abstract

Big data analytics (BDA) is increasingly central to decision-making in higher education, enabling institutions to process and analyze large datasets to improve operations and outcomes. This study aimed to assess awareness and preparedness for predictive analytics in Nigerian universities. A non-experimental descriptive survey design was employed, targeting academic and top-level non-academic staff drawn purposively from university employees. Data were collected via a self-developed questionnaire—Big Data and Assessment for Learning in Nigerian Higher Institutions Questionnaire (BiDAL; reliability coefficient = 0.96)—administered through Google Forms; research questions were analyzed using percentages and frequencies, and hypotheses were tested with chi-square statistics. Key findings indicate an average level of awareness of predictive analytics across higher education institutions, alongside established preparedness for deploying predictive analytics to improve educational assessment. The study concludes that Nigerian universities demonstrate baseline readiness for predictive analytics despite moderate awareness levels. The contribution/implication is the provision of empirical evidence on institutional awareness and preparedness that can inform subsequent assessment, planning, and implementation efforts within Nigerian higher education.

Keywords: Big Data Analytics; Predictive Analytics; Higher Education; Awareness; Preparedness; Descriptive Survey; Chi-Square Analysis; Nigeria

INTRODUCTION

Data helps people, organisations, and governments make good decisions. Over the past 30 years, massive amounts of data have been collected on every aspect of modern life. Millions of people share and store texts, photos, and videos every minute, especially on social media platforms which could be simple, complex or heterogeneous data from different geographical regions results into large datasets also known as 'big data' (Sivarajahet al., 2017).Cope and Kalantzis (2016) define big data as novel methods for gathering, storing, distributing, managing, and analysing massive data volumes in various formats. Big data are enormous datasets that regular software cannot acquire, store, manage, or analyse (Manyika et al., 2011). These massive, heterogeneous, and complicated data collections can be structured, semi-structured, and unstructured. Big data is a key frontier for innovation, research, and development across industries. Big data and analytics (BDA) continue to interest researchers and practitioners. Educational organisations are realising they can process and analyse massive data quantities to benefit their operations and people (George et al., 2014). Worthy of note is the fact that big data leverage on technology to seamlessly capture process, analyse, and visualize potentially large datasets (Baig et al., 2020).

Big data is the foundation upon which artificial intelligence, commonly referred to as AI, is built. Artificial intelligence (AI) models and algorithms cannot be refined, nor can they work effectively or accurately, without big datasets. The seven V's are the characteristics that can be used to define big data (Vassakis et al., 2018). These seven V's include volume, variety, veracity, velocity, variability, visualisation, and value. The term "volume" refers to the vast size of the datasets, which is a large amount of information that is difficult to store, process, analyse, and present. "variety" refers to the growing diversity of data creation sources and data formats, which focuses on whether the data is structured or unstructured. The dependability and correctness of the data (trust, biases, and uncertainty in the data) are what are meant by the term "veracity of data." One of the characteristics that defines velocity is the rapidity with which data is generated, which is related to the increasing rate at which information is transferred throughout an organisation. There is a correlation between the quick shift of meaning and variability. It is possible, for instance, for words in a text to have a distinct meaning depending on the context of the text. Visualisation is the science of visually representing data and information in some schematic form, indicating patterns, trends, anomalies, constancy, variation, in ways that cannot be presented in other forms like text and tables (Gantz, 2011) and *Value* refers to usefulness of data generated for guiding decision making.

The concepts of educational data mining, structured and unstructured data, and supervised and unsupervised learning are intimately related to big data. The term "educational data mining" refers to the methods, tools, and research that are designed to automatically extract meaning from massive repositories of data that are generated by or related to the earning activities of individuals (learning assessment) in educational settings (Esomonu et al., 2020; Şahİn & Yurdugül, 2020). One of the driving forces behind the implementation of innovative teaching, learning, and evaluation methodologies was the aspiration of students to acquire the skills necessary for the 21st century. Large amounts of data are produced as a result of evaluation in the learning environment. Big data in assessment refers to data on learners that is both comprehensive and in-depth (United Nations Educational, Scientific and Cultural Organization-UIS, 2017). This comprehensive data is derived from a variety of sources, including internal examinations and assessments, electronic feedback of students' evaluations, online end-of-term results of students, formative test scores created by teachers, and performance test indicators collected through classroom assessment techniques. Therefore, an online learning platform is essential in order to provide the easy access to students' assessments and to ensure that they are continuously reviewed and especially in crisis situation (Emmanouil & Nikolaos, 2015; Sharadgah & Sa'di, 2020). Assessment big data are generated in quantum computing through the continuous assessment of student learning and the following feedback in the form of assessment findings (Cresswell et al., 2015). The technological advancements of today make it possible for educational institutions to derive insights from data with levels of sophistication, speed, and accuracy that were previously considered impossible (Arroway et al., 2015; Jacqueline, 2012; King & South, 2017). Students, computer programmes, and computer systems are all contributing to the generation of important information as technologies continue to permeate every aspect of higher education (Lesjak et al., 2021).

Big Data brings new opportunities and challenges for institutions of higher education. Long & Siemen (2011) indicated that Big Data presents the most dramatic framework in efficiently utilizing the vast array of data and ultimately shaping the future of higher education. The application of Big Data in tertiary institutions was also echoed by Wagner & Ice (2012), who noted that technological developments have certainly served as catalysts for the move towards the growth of analytics in tertiary institutions of higher education. The implementation of predictive analytics in Nigerian universities is still in its early stages, with a growing awareness of its potential to improve student outcomes, resource management, and institutional efficiency (Oladokun & Adebiyi, 2020). There are a few notable case studies and initiatives in Nigeria where predictive analytics is being explored or implemented to enhance education, which includes : (i) Obafemi Awolowo University (OAU), Ile-Ife, this institution has initiated data-driven projects, including elements of predictive analytics, as part of its efforts to enhance student performance and institutional operations. OAU collects student performance data from its academic systems and uses predictive models to analyze trends in student outcomes, particularly in key courses such as engineering, medicine, and law. The analytics platform identifies students who may struggle academically, enabling the university to provide early academic support and intervention. (ii) University of Ibadan (UI) the University of Ibadan, Nigeria's oldest university, has been implementing digital learning systems and exploring data analytics to enhance student success, including the early adoption of predictive analytics in academic monitoring. UI uses student data from digital platforms, such as LMS, and combines it with academic records to predict student performance. Predictive models help identify students who may be at risk of academic failure based on trends in their engagement with course materials, attendance, and grades. (iii) Lagos State University (LASU) has been exploring the use of data analytics as part of its broader digital transformation agenda, aimed at enhancing academic success and student outcomes. LASU uses a combination of student data, such as grades, attendance, and extracurricular engagement, to build predictive models that assess students' risk of failing or dropping out. (iv) Covenant University leverages its Learning Management System (LMS) and other digital platforms to collect student data, such as attendance, grades, and online engagement.

There some universities outside Nigeria that have successfully implemented predictive analytics, providing valuable insights into how data can improve academic and administrative outcomes among them are: University of the Witwatersrand (Wits), South Africa, Stellenbosch University, South Africa, University of Pretoria, South Africa, University of Nairobi, Kenya, Eduze Africa - Partnership with Universities Across Africa, Georgia State University (GSU), Arizona State University (ASU) etc. Researches also shown that Government institutions often have greater awareness of predictive analytics compared to private ones because of the Access to Larger Data Sets, Government Funding and Resources, National Policies and Initiatives, Centralized Data Collection, Collaborations with International Organizations and Access to National and Regional Data. Despite these broad trends, it's important to acknowledge that not all universities may be equally interested or capable of implementing data analytics, this may be due to Budget Constraints, Lack of Technical Expertise, Different Priorities and Institutional Resistance while many universities are pursuing or considering the implementation of data analytics, the extent of interest and ability to adopt these tools varies across institutions (Ferguson, 2013). Although, numerous activities of students, teachers in the school system, lecturers in tertiary institutions, and the environment of education all contribute to the generation of big data in the Nigerian educational system. During admission processes, students provide their bio data by filling in forms in hard copies or captured online. The Post-unified Tertiary Matriculation Examination is another screening process for most Nigerian universities. Many universities register candidates online, administer computer-based exams, and publish results online. Admitted candidates register online for the first and future registrations. Administrative and teaching staff document extensively. Education institutions conduct annual worker appraisals and generate lots of data (Esomonu et al., 2020).

Big data analytics is an emerging trend in education that analyses enormous data sets to find hidden patterns and other useful information. It processes organised and unstructured data from many sources. Academic Analytics (AA), Educational Data Mining (EDM), and Learning Analytics overlap in education. Big data for assessment and learning through predictive analytics can transform Nigerian universities by personalising learning, boosting retention, and optimising resource allocation (Caspari-Sadeghi, 2023; Lawson et al., 2016). AA is concerned with improving organizational effectiveness through the use of student academic and institutional data; EDM involves actionable intelligence to improve data selection and management while AA is concerned with improving organizational effectiveness through the use of student academic and institutional data. All three have a common goal: to use educational data to understand and improve processes, outcomes, and decisions. Liberatore & Luo (2011) is of the view that a well-developed analytics program translates data into analysis, analysis into insight, and insight into managerial actions, such as improving operational decisions, redesigning or changing existing processes, formulating or adjusting strategies, or improving decision quality and speed. Data analytics can be descriptive, diagnostic, predictive, and prescriptive (El More et al., 2021; Funmilola & David, 2019; Gaming, 2022). Descriptive analytics answers the question "What happened?" by summarizing historical data to answer "What happened?" Diagnostic analytics addresses "Why did this happen?" and explains descriptive analytics patterns and correlations. Predictive and prescriptive analytics address "What might happen in the future?" and "What should we do next?". These components show that data analytics has the greatest potential when it is developed and embedded in normalized educational processes.

Assessment for learning is also one of the areas in education where big data and learning analytics are found very useful. Assessment for learning is an assessment that supports learning through continuous monitoring of student learning using feedback to improve performance (Daramola et al., 2019; Macfadyenet al., 2014). According to O'Reilly and Veeramchanet (2014), assessment for learning comprises all actions carried out by teachers and students that offer feedback for the purpose of altering teaching and learning activities that take place in the classroom. In contrast to assessment of learning, which is primarily designed to serve the purpose of accountability, grading students' performance, and passing judgement on standard of performance, it is a part of everyday practice, where students, teachers, and peers seek, reflect, and respond to information from assessment tasks to enhance ongoing learning. This is in contrast to assessment of learning, which is designed to serve the purpose of evaluating students' performance. The assessment of learning is essential for students to acquire the 21st century competences, which include learning how to learn, thinking about their own learning, being able to plan and evaluate their thinking and knowledge, and learning how to manage their own learning (Oladele et al., 2022).

In the context of assessment, big data refers to learner data that is deep and broad. A large amount of data that occurs across a large number of learners in the form of test and examination scores can be considered to be broad. On the other hand, data that occurs within individual learners, such as problem-solving processes, misconceptions, background information, and other behavioural and contextual information, can be considered to be deep. (Ugodulunwa et al., 2019). Data enriched assessment requires that deeper and broader data be collected in order to gain insight into new object of assessment (Thille et al., 2014). Through the provision of ongoing diagnostic information on learners' knowledge and related behaviour, as well as through the promotion of learning through focused feedback that is made feasible through online learning environments, the authors claim that big data enriches the assessment process. Through online learning platform, a student's learning process, such as contributions to a discussion forum, learning sessions, steps in problem-solving, interactions with learning resources, peers, or teachers and evidence of concepts and skills that are mastered by students can be continually monitored (Baig et al., 2020). Big data and learning analytics have great promise in online learning environments because meaningful information across and within learners provide a strong basis for assessment for improving students' learning. This potential can be realized by embedding assessment for learning within the instructional process for supporting teaching and learning, which is very effective when big data analytics is employed. Sources of big data in education have been identified which include demographics, such as age, sex, location and professional background, database systems that store large longitudinal data on students, learning activities and teaching, students' behaviour test and examination results, teaching materials, as well as enrollment information and educational needs. Big data can be collected from learning management system (LMS), Blackboard (BB) Learn, Moodle and Massive Open Online Courses (MOOC), among other platforms to enable teachers' study and compare several assessment outcomes for all students within class and across class (Arranz & Alonso, 2013; Daniel, 2017).

There are proposed framework or models for implementing predictive analytics in higher education, which could contribute to both the originality and practical applicability of the research. These includes the comprehensive data-driven student success framework (CDSS Framework) which focuses on integrating all aspects of student data, from academic to socio-economic factors in order to provide a holistic and personalized approach to improving student outcomes. Also, academic-administrative data integration (AADI) is another framework which aids the integrating both academic and administrative data to streamline operations and improve both student success and institutional decision-making.

The AI-powered adaptive learning model (AAL) model introduces AI-driven adaptive learning technologies that adjust the educational experience to each student's learning style and pace, improving the effectiveness of predictive analytics in student success. Furthermore, the equity-focused predictive analytics (EFPA) model aims to address the equity gaps in higher education by using predictive analytics to identify and support students from disadvantaged backgrounds, ensuring that interventions are targeted and impactful. Also, we have the multi-stakeholder predictive analytics collaboration (MPAC) framework. This framework proposes a collaborative approach involving not just the university but also external stakeholders such as the government, industry, and tech companies to leverage predictive analytics effectively. Any of these frameworks can be engaged for managing institutional data having considered specific needs. This is germane as Ugodulunwa et al. (2019) and Macfadyen et al. (2011) found that the huge amounts of data collected in the field of education are not utilised for decision making stressed that the emergence of big data and analytics is a welcome development that has the potential to assist in the utilisation of a wide variety of data that has been collected but is not currently being utilised for the purpose of addressing the issue of students' low performance and attrition in Nigerian education. Daniel (2015) also highlighted the need for different stakeholders in higher education institutions to respond to educational issues in a timely manner to these demands, taking into consideration the current decrease in government funding, the decreasing support from business and private sectors, the growing regulatory demands for transparency and accountability, the declining admissions rates due to increasing tuition and operational cost, and the upsurge in high school dropouts. The purpose of this study is to investigate the awareness and preparedness for predictive analytics in Nigerian universities. Specifically, the study sought to examine:

1. level of university awareness of predictive analytics in Nigeria;
2. the extent can predictive analytics improve the assessment process in Nigerian University; and
3. level of universities preparedness in implementing predictive analytics in Nigeria?

Research Questions

1. What is the level of university awareness of predictive analytics in Nigeria?
2. To what extent can predictive analytics improve the assessment process in Nigerian University?

3. What is the level of universities preparedness in implementing predictive analytics in Nigeria?

Research Hypotheses

Hypothesis One: There is no significant difference in universities staff level of awareness of predictive analytics based on institution ownership.

Hypothesis Two: There is no significant difference in the level of universities preparedness in implementation of predictive analytics based on institution ownership

METHODOLOGY

This study adopts a descriptive survey research design. The study population were students across the levels and senior academic/non-academic staff in higher institutions in North-central Nigeria using a multi-stage sampling procedure consisting of cluster and purposive sampling techniques. A self-developed questionnaire titled Big Data and Assessment for Learning in Nigerian Higher Institutions Questionnaire "BiDAL" was the instrument used for data collection. The instrument had an overall reliability coefficient of 0.96. The instrument was administered using online surveys by sharing the link to the survey on student and university staff WhatsApp groups which were leveraged as target clusters. Considering the volatility with the reach of online forms, the collated data was curated to ensure that only responses from university-level students and staff in North Central Nigeria were collected. The curated data was analysed using descriptive of the frequency and percentages to answer the research questions while the inferential statistics of chi-square were used to test the hypothesis generated for the study at 0.05 level of significance.

RESULTS

One hundred and sixty-two responses were received. The data curation process was purpose-driven to include only responses from students and staff from universities in North-Central Nigeria and the data curation resulted into one hundred and forty-nine responses were found viable. Therefore, a data collection had a 91.2% success rate. The collected data were analysed to answer the raised research questions and used to test the generated study hypotheses as follows.

Research Question One: What is the level of awareness of predictive analytics?

Table1: Level of Universities awareness of predictive analytics

Awareness	Frequency	Percentage
Aware	36	24.2
Somewhat Aware	78	52.3
Not Aware	35	23.5
Total	**149**	**100**

It is shown in Table 1 that 36 (24.2%), 78 (52.3%) and 35 (23.5%) of the respondents were respectively aware, somewhat aware and not aware of predictive analytics. It implies that University staff are somewhat aware of predictive analytics because a little above average of the respondents indicated that.

Research Question Two: To what extent can predictive analytics improve the assessment process?

Table 2: Extent of improvement of predictive analytics on assessment process

Improvement	Frequency	Percentage
Yes/High	92	61.7
No/	7	4.7
Not Sure	50	33.6
Total	**149**	**100**

It is shown in Table 1 that 92 (61.7%), 7(4.7%) and 50 (33.6%) of the respondents respectively submitted that predictive analysis can improve assessment process, cannot improve assessment process and not sure of improving assessment process. Hence, predictive analysis can improve assessment process since 61.7% of the respondents indicated that.

Research Question Three: What is the level of universities preparedness in implementation predictive analytics?

Table 3: level of Universities Preparedness in implementation of predictive analytics

Improvement	Frequency	Percentage
Not Prepared	15	10.1
Slightly Prepared	17	11.4
Moderately Prepared	69	46. 3
Prepared	33	22.1

Improvement	Frequency	Percentage
Very Prepared	15	10.1
Total	**149**	**100**

It is shown in Table 3 that 15 (10.1%), 17 (11.4%), 69 (46.3%), 33(22.1%) and 15 (10.1%) of the respondents respectively submitted that university is not prepared, slightly prepared, moderately prepared, prepared and very prepared for predictive analytics implementation. It can be deduced that level of preparedness of the universities in implementation predictive analytics is moderate because more respondents (46.3%) of the participants indicated that.

Hypotheses Testing

Hypothesis One: There is no significant difference in universities staff level of awareness of predictive analytics based on institution ownership

Table 4: Chi Square showing difference in universities staff level of awareness of predictive analytics based on institution

Level of Awareness	Federal University	State University	Private University	Total	df	Chi Square value	p-value	Decision
Very Familiar	27	9	0	36				
Somewhat Familiar	63	6	9	78	4	12.06	0.02	Rejected
Not Familiar	29	2	4	35				
Total	**119**	**17**	**13**	**149**				

As shown in Table 4, the chi-square value of 12.06 with p-value is 0.02 which is less than the significant value of 0.05 (0.000<0.05) was revealed in Table 4. The null hypothesis that stated that there is no significant difference in universities staff level of awareness of predictive analytics based on institution ownership is therefore rejected. Hence there is significant difference in universities staff level of awareness of predictive analytics based on institution ownership. Federal University staff is significantly somewhat familiar with predictive analytics.

Hypothesis Two: There is no significant difference in the level of universities preparedness in implementation of predictive analytics based on institution ownership

Table 5: Chi Square showing difference in universities staff level of awareness of predictive analytics based on institution

Level of Awareness	Federal University	State University	Private University	Total	df	Chi Square value	p-value	Decision
Not Prepared	11	3	1	15				
Slightly Prepared	12	3	2	17				
Moderately Prepared	57	6	6	69				
					8	3.06	0.93	Accepted
Prepared	26	4	3	33				
Very Prepared	13	1	1	15				
Total	**119**	**17**	**13**	**149**				

Table 5 showed a chi-square value of 3.06 with p-value is 0.93 which is greater than the significant value of 0.05 (0.93>0.05). The null hypothesis two that stated that there is no significant difference in the level of universities preparedness in implementation of predictive analytics based on institution ownership is therefore accepted. Hence there is no significant difference in the level of universities preparedness in implementation of predictive analytics based on institution ownership.

DISCUSSION

The first finding from this study showed that university staff are somewhat aware of predictive analytics because a little above average of the respondents indicated that. This finding is at par with that of Ugodulunwa et al. (2019) which showed that university teachers are not aware of different sources of big data that can be used in assessment learning, such as student academic background information, disciplinary record, demographic characteristics, grades, online social interactions and online discussion forum, as well as unstructured data such as documents, emails and video that enable teachers get insight into students' learning and The standard deviations reveal that the teachers were performance. This finding corroborates is further corroborated by the views of Macfadyen et al. (2011) found that the huge amounts of data collected in the field of education are not utilised for decision making. In the event that big data is utilised for decision making in an efficient manner, educators would be aware of many sources of big data that are both extensive and in-depth.

With respect to extent can predictive analysis improve the assessment process, the findings from this study revealed that predictive analysis can improve assessment with majority of the respondents affirming that. This finding aligns with the report given by Mayinka et al., (2011) which revealed that the utilisation of big data for assessment and learning through predictive analytics has the potential to revolutionise Nigerian universities by virtue of its ability to personalise learning, increase retention rates, and optimise resource allocation. Similarly, data mining techniques and tools are required for improving educational effectiveness and improves its system. This submission further brings to bear the importance of leveraging technological advancements within the higher education space in line with the submission of Baig (2020).

Furthermore, on the level of universities preparedness in implementation predictive analytics, preparedness of the universities in implementation predictive analytics is moderate with close to half of the participants affirming that. The finding is germane considering that Emmanouil & Nikolaos (2015) identified preparedness as central to the usage of Big Data especially in crisis situation. There is a clear deviation between the findings of this study and that of Sharadgah & Sa'di (2020) which showed that faculty members in institutions in United Arab had a high level of preparedness.

Findings from the tested hypotheses on universities staff level of awareness of predictive analytics based on institution ownership was significant in favour of federal-owned universities. While the significance in awareness could be alluded to the higher number of study participants, higher institutions should leave no stone unturned to ensure that the gains of predictive analytics are leveraged for academic improvements. The findings based on level of universities preparedness in implementation of predictive analytics was not significant. The non-significance recorded shows that irrespective of institutional ownership, universities are prepared to implement predictive analytics using big data.

CONCLUSION

Based on the findings of this study, this study therefore concluded that there is an average awareness of and preparedness for predictive analytics within the higher education institutions in Nigeria for predictive analytics in improving educational assessment was established. There is however a need to raise the level of preparedness of the universities in implementation predictive analytics. This is further strengthened as all the universities want the implementation of predictive analytics using big data. To improve awareness of big predictive analytics in higher education institutions in Nigeria, it is recommended that the university administration should organise workshops and training programs, engage in curriculum integration, create awareness campaigns, create data analytics centres and research and publications.

REFERENCES

Arranz, O., & Alonso, V. (2013). Big Data & Learning Analytics: A Potential Way to Optimize eLearning Technological Tools. IADIS International Conference e-Learning 2013 https://bit.ly/2VweSsw7

Arroway, P., Morgan, G., O'Keefe, M., & Yanosky, R. (2015). Learning analytics in higher education (p. 17). Research report. Louisville, CO: ECAR, March 2016.

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2020). Big data in education: a state of the art, limitations, and future research directions. *International Journal of Educational Technology in Higher Education, 17*, 1-23. https://doi.org/10.1186/s41239-020-00223-0

Caspari-Sadeghi, S. (2023). Learning assessment in the age of big data: Learning analytics in higher education. *Cogent Education, 10*(1), 2162697.https://doi.org/10.1080/2331186X.2022.2162697

Cope, B. & Kalantzis, M. (2016). Big data comes to school: Implications for learning, assessment and Research.

Cresswell, J.; Schwantner, U. & Waters, C. (2015). *A review of international large-scale assessments in education: assessing component skills and collecting contextual data*. Paris: Organization for Economic Co-operation and Development.https://doi.org/10.1787/9789264248373-en

Daniel, B. (2015). Big Data and analytics in higher education: Opportunities and challenges. *British journal of educational technology, 46*(5), 904-920.https://doi.org/10.1111/bjet.12230

Daniel, B. K. (2017). Overview of big data and analytics in higher education. In B. K. Daniel (Ed.), *Big data and learning analytics in higher education: Current theory and practice* (pp. 1–4). Springer, Cham.

Daramola, D. S., Oladele, J. I., & Owolabi, H. O. (2019). Effect of assessment for learning strategy on children's learning outcomes in mathematics in Private-Owned ECCE

Centers in Ilorin South Local Government Area, Kwara State. *International Journal of Psychology and Education, 3*(03).

Eleje, L. I.; Esomonu, N.P.M. & Ufearo, F.N. (2019). Trends in information and communication technology and learning assessment: the application and implication. *International Educational Applied Research Journal (IEARJ),* 3, (11).

El Morr, C., Ali-Hassan, H., El Morr, C., & Ali-Hassan, H. (2019). Descriptive, predictive, and prescriptive analytics. Analytics in healthcare: a practical introduction, 31-55.https://doi.org/10.1007/978-3-030-04506-7_3

Esomonu, N. P. M., Esomonu, M. N. & Eleje, L. I. (2020). Assessment big data in Nigeria: Identification, generation and processing in the opinion of the experts. *International Journal of Evaluation and Research in Education (IJERE)*, 9 (2), 345-351.https://doi.org/10.11591/ijere.v9i2.20339

Ferguson R. (2013), Learning Analytics, drivers, developments and Challenges; International *Journal of Technology Enhanced learning 4(5/6) pp 304-317.*

Funmilola, B. A., & David, A. A. (2019, August). Evaluation of diagnostic analysis and predictive analysis for decision making. *In Conference on Transifion from observafion to Knowledge to Intelligence*, University of Lagos (pp. 15-16).

Gaming, L. (2022) Descriptive, Diagnostic, Predictive and Prescriptive Analytics.https://www.scribd.com/document/574859175/Unit-V

Gantz, J. (2011). Extracting Value from Chaos. The IDC iView. http://idcdocserv.com/1142

George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. Academy of management Journal, 57(2), 321-326.https://doi.org/10.5465/amj.2014.4002

Jacqueline, B. (2012). Analytics in Higher Education: Benefits, Barriers, Programs and Recommendations.

King, J., & South, J. (2017). Reimagining the role of technology in higher education: A supplement to the national education technology plan. *US Department of Education, Office of Educational Technology,* 1-70. http://tech.ed.gov

Lawson, C., Beer, C., Dolene, R., Moore, T., & Fleming, J. (2016). Identification of "At Risk" students using learning analytics: The ethical dilemmas of intervention strategies in higher education institution. *Educational Technology Research & Development*, 64(5), 957–968.https://doi.org/10.1007/s11423-016-9459-0

Lesjak, D., Natek, S., & Kohun, F. (2021). Big data analytics in higher education. *Issues in Information Systems, 22*(4).https://doi.org/10.48009/4_iis_2021_346-359

Liberatore, M.J. & Luo, W. (2011). The Analytics Movement: Implications for Operations Research. Interfaces, 40(4), pp. 313- 324.

Long, P. & Siemen, G. (2011). Penetrating the fog: analytics in learning and education. EDUCAUSE Review, 46, 5, 30–40.

Macfadyen, L.P., Dawson, S., Pardo, A. and Gasevi, D. (2014). Embracing big data in complex educational systems: The learning analytics imperative and the policy change. *Research and Practice in Assessment,* 9(2): 17-28.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A.H. (2011). *Big Data: The Next Frontier for Innovation, Competition, and Productivity.* (Research Report). McKinsey Global Institute, June 2011.

Nithya, P., Umamaheswari, B. and Umaderi, A. (2016). A survey on educational data mining in field of education. *International Journal of Advance Research in Computer Engineering and Technology (IJARCET),* 5 (1), 69-78.

O'Reilly and K. Veeramchanet, (2014). Technology for mining the big data of MOOCs

Oladele, J. I., Ndlovu, M., & Ayanwale, M. A. (2022). Computer adaptive-based learning and assessment for enhancing STEM education in Africa: a fourth industrial revolution possibility. *In Mathematics Education in Africa: The Fourth Industrial Revolution* (pp. 131-144). Cham: Springer International Publishing.10.1007/978-3-031-13927-7_8

Oladokun, S. O., & Adebiyi, A. (2020). *Building Capacity for Big Data Analytics in Nigerian Higher Education: Challenges and Opportunities. Journal of Educational Technology & Society*, 23(4), 140-156.

Şahİn, M., & Yurdugül, H. (2020). Educational data mining and learning analytics: past, present and future. *Bartın University Journal of Faculty of Education, 9*(1), 121-131. DOI: https://doi.org/10.14686/buefad.606077

Sharadgah, T. A., & Sa'di, R. A. (2020). Preparedness of institutions of higher education for assessment in virtual learning environments during the Covid-19 lockdown: Evidence of bona fide challenges and pragmatic solutions. *Journal of Information Technology Education: Research,* 19. https://doi.org/10.28945/4615

Siemens, G. (2011). How data and analytics can improve education, July 2011. Retrieved August 8, October 30, 2014, from http://radar.oreilly.com/2011/07/education-data-analytics-learning.htm

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of business research, 70*, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.001

Thille, C., Schneider, E., Kizilcec, R. F., Piech, C., Halawa, S. A., & Greene, D. K. (2014). The future of data-enriched assessment. *Research & Practice in Assessment, 9*, 5-16. https://www.rpajournal.com/dev/wp-content/uploads/2014/10/A1.pdf

Ugodulunwa, C. A., Anikweze, C. M., Francisca, N. O., Eucharia, E. L., Ntasiobi, C. I., Uwaleke, C. C., ... & Eze, A. (2019). Big data and assessment for learning in Nigerian Universities: Prospects and challenges. *American-Eurasian Journal Agriculture & Environmental Science, 19*(3), 224-232. https://doi.org/10.5829/idosi.aejaes.2019.224.232

United Nations Educational, Scientific and Cultural Organization-UIS (2017). The Quality Factor: Strengthening National Data to Monitor Sustainable Development Goal 4. https://uis.unesco.org/sites/default/files/documents/quality-factor-strengthening-national-data-2017-en.pdf

Vassakis, K., Petrakis, E., & Kopanakis, I. (2018). Big data analytics: applications, prospects and challenges. Mobile big data: *A roadmap from models to technologies,* 3-20. https://doi.org/10.1007/978-3-319-67925-9_1

Wagner, E. & Ice, P. (2012). Data changes everything: delivering on the promise of learning analytics in higher education. EDUCAUSE Review, July/August, 33–42.