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ENHANCING DISTANCE LEARNING ENGAGEMENT THROUGH LEARNING ANALYTICS IN DISTANCE LEARNING CENTRES IN ENUGU STATE, NIGERIA

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ABSTRACT

Distance learning has expanded the opportunities available to learners who may be unable to participate conveniently in conventional face-to-face education. However, maintaining students' active participation, persistence, interaction and commitment remains a major challenge in distance education. Learning analytics provides an emerging approach for understanding learners' activities through the systematic collection, measurement, analysis and interpretation of educational data. This study examined how learning analytics can enhance distance learning engagement in distance learning centres in Enugu State. The study adopted a descriptive survey research design. Three purposes, three research questions and three null hypotheses guided the study. The population for the proposed study comprised distance learning students enrolled in selected distance learning centres in Enugu State. A structured questionnaire titled *Learning Analytics and Distance Learning Engagement Questionnaire (LADLEQ)* was used as instrument for data collection. Data were analysed using mean and standard deviation with the null hypotheses tested at the 0.05 level of significance. The study focused on three dimensions of learning analytics: learning activity monitoring, personalized feedback and early identification of disengagement. The findings of the study revealed that responsible use of learning analytics, combined with timely instructional intervention, personalized feedback, learner support and appropriate privacy safeguards, can contribute to stronger engagement in distance education. The study recommends that distance learning centres establish learning-analytics dashboards, train staff in data-informed student support, provide timely personalized feedback, identify disengaged learners early, and establish transparent policies for student data privacy and informed consent.

Keywords: Learning Analytics, Distance Learning, Student Engagement, Online Learning, Personalized Feedback, Learning Activity Monitoring, Enugu State.

1 INTRODUCTION

The expansion of information and communication technologies has transformed the organization, delivery and management of higher education. One of the most significant developments has been the growth of distance learning, which provides learners with opportunities to study without being physically present in conventional classrooms throughout the learning process. Distance education enables institutions to extend educational opportunities to working adults, geographically dispersed learners, individuals with family responsibilities and other students whose circumstances may make regular face-to-face attendance difficult (Palanci, Yılmaz, & Turan, 2024). Through online platforms, digital learning resources, discussion forums, recorded lectures, electronic assessments and other technologies, learners can increasingly participate in educational activities beyond the traditional classroom. Despite these opportunities, student engagement remains an important concern in distance learning (Bergdahl, Bond, Sjöberg, Dougherty, & Oxley, 2024). Access to educational materials does not automatically translate into active participation or successful learning. Students may register for online courses, access learning platforms occasionally and still demonstrate limited participation in discussions, assessments, collaborative activities and other learning tasks (Mohamad, Sazali, & others, 2023). Some learners may gradually disengage without being immediately noticed by lecturers or administrators. Consequently, distance learning institutions need reliable ways of understanding learners' participation and identifying students who may require additional academic or motivational support.

Student engagement is generally regarded as a multidimensional construct involving behavioural, cognitive, emotional and social dimensions. It can involve behavioural participation, cognitive investment, emotional involvement and social interaction. In distance education, behavioural engagement may include logging into a learning-management system, accessing course materials, submitting assignments and participating in discussion forums (Johar, Kew, Tasir, & Koh, 2023). Cognitive engagement may involve students' effort to understand difficult concepts, reflect on course content and apply knowledge. Emotional engagement can involve interest, enthusiasm and a sense of belonging, whereas social engagement can be reflected in interaction with lecturers and fellow learners (Bergdahl et al., 2024). The multidimensional nature of engagement creates difficulties for institutions attempting to monitor students in distance-learning environments. In conventional classrooms, lecturers may observe attendance, participation, facial expressions and interaction directly. In online and distance environments, many of these observations are unavailable. Johar et al. (2023) posited that digital learning environments, however, generate large quantities of data concerning student activities. These data may include login frequency, time spent on learning resources, assignment submissions, quiz attempts, discussion participation, page views and patterns of interaction. Learning analytics provides a mechanism for converting such data into information that can support teaching and learning decisions.

Learning analytics may broadly be understood as the collection, measurement, analysis and reporting of data about learners and their learning contexts for purposes of understanding and improving learning. Its importance has increased as educational institutions have adopted learning-management systems and other digital platforms. Ifenthaler and Yau (2020) observed that learning analytics can be used to support study success by examining factors associated with learners' educational activities and outcomes. Their systematic review demonstrated the growing use of learning analytics in higher education to support different aspects of student success. Learning analytics can provide lecturers and administrators with information that would otherwise be difficult to obtain. For example, a lecturer may identify students who have not accessed learning materials for several weeks, students who repeatedly fail online assessments or learners who participate actively in one component of a course but withdraw from another. Such information can provide an opportunity for early intervention.

The relevance of learning analytics to student engagement has received considerable attention in recent scholarship. A systematic review by Holloway (2020), examining learning analytics and student engagement reported that analytics can be used to identify different types of engagement and potentially support improved learning performance. The review nevertheless observed that multifaceted approaches to engagement remain relatively limited. More recently, Bergdahl et al. (2024) stated that learning analytics research predominantly uses observable behavioural indicators such as clicks, task duration and other digital traces. Behavioural engagement appeared substantially more frequently than cognitive, emotional or social engagement. The authors therefore cautioned against assuming that digital activity alone provides a complete representation of student engagement. This observation is particularly relevant to distance learning centres. A student who logs into a learning platform frequently is not necessarily cognitively engaged with the learning content. Similarly, a student who spends little time online may nevertheless download materials and study them offline. Therefore, learning analytics should not be interpreted mechanically. Rather, analytics should be combined with professional judgement, learner feedback and contextual information.

One important application of learning analytics is learning activity monitoring. Learning-management systems can record information about learners' interactions with educational resources. Such information can provide lecturers with an overview of student participation. When appropriately interpreted, activity data can help lecturers recognise participation patterns and determine where additional support may be required. Munawar (2021) defines learning activity monitoring as the regular observation of students' activities within an e-learning system, particularly their attendance, assignment submission, and participation in quizzes, to track their learning progress. Matsumoto et al. (2025) describe learning activity monitoring as the analysis and visualization of students' learning activity records, such as class participation and assignment submission, to identify students whose level of activity may require early support.

A second application is personalized feedback. Learning analytics can support the provision of information to learners about their progress, assessment performance and participation. Instead of providing identical feedback to all students, lecturers may use analytics to identify particular learning needs. For example, a learner who repeatedly performs poorly on a particular topic may receive targeted resources, additional explanations or recommendations for remedial activities. Banihashem et al. (2022) reported that learning analytics has an important role in improving feedback practices in higher education. Their systematic review found that information visualisation is frequently used in analytics-based feedback systems and that analytics-supported feedback can serve both students and educators. Tetzlaff, Schmiedek and Brod (2021) explain personalized instruction as the adjustment of teaching to the characteristics of an individual learner. Therefore, personalized feedback can be understood as feedback tailored to a learner's specific needs, characteristics and learning performance. Lim et al. (2020) describe personalized feedback in learning analytics as feedback provided to students based on their individual learning activities and behavioural data, with the aim of helping them understand their learning and improve their self-regulated learning processes.

A third important application is early identification of disengagement. Distance-learning students may discontinue participation because of academic difficulties, technological problems, financial pressures, employment responsibilities, lack of motivation, inadequate interaction or other circumstances. Analytics may identify changes in participation before complete withdrawal occurs. For example, a sudden reduction in login activity, missed assignments and declining assessment attempts may constitute indicators that a learner needs assistance. Atif et al. (2020) describe early identification of disengagement as the timely use of learning-management-system data to identify students who may be at risk and require academic support or intervention. Linden, van der Ploeg and Roman (2023) describe early identification of disengaged students as the use of explainable learning analytics to detect students showing early signs of reduced participation, such as failure to access the LMS or submit an early assessment.

The use of analytics to support students at risk of academic difficulties is consistent with the broader objective of learning analytics. Ifenthaler and Yau (2020) noted that analytics can support understanding of factors related to study success. However, learning analytics should not merely identify students as "at risk"; institutions should also have mechanisms for responding constructively to the information generated. The effectiveness of analytics therefore depends partly on institutional capacity. If a dashboard identifies a disengaged student but no lecturer, adviser or support officer follows up with that learner, the analytical information may have little practical value. Thus, learning analytics should be integrated into a broader student-support system involving lecturers, academic advisers, technical support personnel and administrators.

The Nigerian context presents particular considerations. Distance learning has considerable potential for widening access to higher education because Nigeria has a large population of learners seeking flexible educational opportunities. Students may combine study with employment, business, family responsibilities and other activities. Distance-learning centres consequently need mechanisms capable of recognising differences in students' participation and learning patterns. In Enugu State, distance-learning centres serve learners from different backgrounds and with varying levels of access to digital technologies. Students may differ in internet connectivity, digital literacy, availability of devices, learning schedules and familiarity with online educational platforms. These differences may affect engagement and should be considered when interpreting learning-analytics data.

Learning analytics can therefore provide an important source of evidence for improving student engagement in these centres. However, its application should be learner-centred rather than surveillance-oriented. Students should understand what data are collected, why the data are collected and how they will be used. Jones et al. (2020) found that students expressed significant concerns about privacy and data use and emphasised the importance of transparency, trust and informed consent. Similarly, Jones (2020) argued that higher education institutions have significant responsibilities concerning the collection and use of students' educational data. Learning analytics should therefore be implemented with appropriate safeguards for privacy, confidentiality, security and responsible data management.

The significance of the present study lies in examining the relationship between learning analytics and engagement within the specific context of distance learning centres in Enugu State. Although international research has increasingly examined learning analytics and engagement, the literature also identifies gaps concerning the measurement of multidimensional engagement and the interpretation of digital traces. Bergdahl et al. (2024) specifically recommended

more comprehensive approaches that move beyond behavioural indicators. This study consequently considers learning analytics from three practical perspectives: monitoring learning activities, providing personalized feedback and identifying disengagement early. These dimensions are examined in relation to distance-learning engagement among students in distance learning centres in Enugu State.

1.1 Statement of the Problem

Distance learning has created opportunities for students to access higher education without the requirement for continuous physical attendance. Nevertheless, the flexibility associated with distance education may create difficulties in maintaining sustained student engagement. Some students may register for courses but participate irregularly in online learning activities. Others may fail to submit assignments on time, participate minimally in discussion activities or discontinue accessing digital learning materials. The problem becomes more complicated because lecturers in distance-learning environments may not have direct opportunities to observe students' learning behaviours.

In a conventional classroom, a lecturer may notice when a student stops attending classes, appears confused, fails to participate or experiences difficulty with a particular topic. In distance education, such indicators may be less visible. The absence of timely information about student engagement can delay intervention. By the time an institution recognises that a student has become disengaged, the learner may already have missed several learning activities or assessments. This may negatively affect academic progress and increase the possibility of withdrawal.

Another problem concerns the limited use of learner-generated digital information for student support. Distance-learning platforms can generate information concerning logins, resource access, assignment submission, quiz participation and discussion activities. However, the existence of data does not necessarily mean that institutions systematically analyse or use it to improve student engagement. There is also a conceptual problem associated with interpreting learning analytics. Digital activity does not necessarily represent all dimensions of engagement. A learner's number of clicks may demonstrate behavioural activity without revealing whether the learner understands the learning material. Bergdahl et al. (2024) found that learning analytics research predominantly measures behavioural engagement, with substantially fewer studies addressing cognitive, emotional and social engagement.

Furthermore, privacy and ethical concerns may affect students' acceptance of learning analytics. Learners may feel uncomfortable if they believe that their online activities are being monitored without adequate information about how the data are used. Jones et al. (2020) reported that students expressed concerns regarding awareness, privacy, data sharing and institutional trust.

In Enugu State, there is therefore a need to understand how learning analytics can be used to support rather than merely monitor distance learners. The problem addressed by this study is the need for evidence concerning the extent to which learning activity monitoring, personalized feedback and early identification of disengagement can contribute to enhanced engagement among students in distance learning centres.

1.2 Purpose of the Study

The general purpose of the study was to examine how learning analytics can enhance distance learning engagement in distance learning centres in Enugu State. Specifically, the study seeks to:

- Determine the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres in Enugu State.
- Determine the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State.
- Determine the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State.

1.3 Research Questions

The following research questions guided the study:

- To what extent does learning activity monitoring through learning analytics enhance student engagement in distance learning centres in Enugu State?
- To what extent does personalized feedback through learning analytics enhance student engagement in distance learning centres in Enugu State?
- To what extent does early identification of student disengagement through learning analytics enhance student engagement in distance learning centres in Enugu State?

1.4 Hypotheses

The following null hypotheses were tested at the 0.05 level of significance:

- **$H_0$1:** There is no significant difference between the mean ratings of distance learners and instructors on the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres in Enugu State
- **$H_0$2:** There is no significant difference between the mean ratings of distance learners and instructors on the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State
- **$H_0$3:** There is no significant difference between the mean ratings of distance learners and instructors on the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State.

2 METHODOLOGY

The study adopted a descriptive survey research design. The study was conducted in distance learning centres in Enugu State, Nigeria. They are: University of Nigeria, Nsukka (UNN) – Centre for Distance and e-Learning (CDeL), Enugu State University of Science and Technology (ESUT) - Open and Distance Learning Centre and First African Distance Learning University (FADLU) Awgu, Enugu State. The target population for this study was 3,786 respondents made up of 3,682 distance learners and 104 instructors in distance learning centres in Enugu State. (**Source:** Nigeria University Commission, 2024). The reason for choosing distance learners and instructors was because they were the categories of people that can give correct information with respect to the subject matter in this study. The sample for this study consisted of 300 respondents made up of 270 distance learners and 30 instructors randomly selected from the three distance learning centres in Enugu State. This sample was drawn using multi-stage sampling procedure. First, the study area was stratified into 3 Senatorial Zones in Enugu (Enugu East Senatorial Zone, Enugu North Senatorial Zone and Enugu West Senatorial Zone). This was to ensure that distance learners and instructors in the various Senatorial Zone were given equal opportunity to participate in the research. Next, one distance learning centre was purposively selected from each of the three Senatorial Zone. In each of the distance learning centres, 90 learners and 10 instructors were randomly selected, making it a total of 270 learners and 30 instructors adopted in the three distance learning institutions. Thus, the sample for the present study is 300 respondents.

The instrument for data collection was the researcher's designed questionnaire titled Learning Analytics and Distance Learning Engagement Questionnaire (LADLEQ). It was made up of three clusters with 5 items on each of them. The questionnaire was structured on a 4-point rating of Strongly Agree (SA) 4 points, Agree (A) 3 points, Disagree (D) 2 points and Strongly Disagree (SD) 1 point. Cluster one focused on the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres in Enugu State. Cluster two hinged on the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State and cluster three focused on extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State. Cronbach alpha statistic was adopted to estimate the internal consistency of the questionnaire. There were three clusters which yielded the following reliability coefficient of 0.91, 0.77 and 0.82 respectively. The average coefficient of all the clusters was 0.83. This shows that the instrument was reliable. The instrument was administered to the respondents by the researcher and three research assistants. A total of 300 copies of the questionnaires were administered and collected on the spot from the respondents. Data obtained were analysed using mean score and standard deviation. In addition, the null hypotheses were tested using t-test statistics at 0.05 level of significance. Any mean score lower than 2.50 implied disagree while equal to or higher than 2.50 implied agree to the items. Similarly, for the testing of null hypotheses. If the t-calculated values are less than critical t-value, null hypotheses were accepted, but if the t-calculated values are more than critical t-value, null hypotheses were rejected.

3 RESULTS

The results of the data analyses were presented based on research questions and hypotheses in tables.

3.1 Research Question One

To what extent does learning activity monitoring through learning analytics enhance student engagement in distance learning centres in Enugu State?

Table 1: Mean ratings on extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres

S/N	ITEMS	Instructors			Learners		
		X	SD	REM	X	SD	REM
1	Student Attendance Monitoring	2.81	0.89	A	3.19	0.95	A
2	Student Login and Platform Access Monitoring	3.22	0.79	A	2.86	1.03	A
3	Assignment Submission Monitoring	3.25	0.69	A	3.35	0.84	A
4	Online Quiz and Test Participation Monitoring	3.12	0.87	A	3.28	0.93	A
5	Learning Material Access Monitoring	3.15	0.84	A	3.34	0.81	A
6	Discussion Forum Participation Monitoring	2.23	0.72	D	2.26	0.96	D
7	Video Lecture Viewing Monitoring	2.28	1.09	D	2.21	0.99	D
8	Time-on-Task Monitoring	3.28	0.73	A	3.20	0.97	A
9	Student–Tutor Interaction Monitoring	3.27	0.66	A	3.39	0.76	A
10	Course Progress and Completion Monitoring	3.28	0.70	A	3.47	0.72	A

X = Mean, SD = Standard Deviation, rem = Remark

Table 1 shows the mean responses and standard deviations of the responses on extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres. Table 1 above shows that since the mean responses of items 6 and 7 are below the criterion mean of 2.50, the respondents disagree with them as the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres, while others with mean responses above 2.50 (criterion mean), indicate that respondents agree with the items as the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres. The standard deviations of the items range from 0.66 to 1.09 indicating that the respondents were not too far from the mean and from one another in their responses.

- **Ho_1:** There is no significant difference between the mean ratings of distance learners and instructors on the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres in Enugu State.

Table 2: t-test of the two groups on the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres in Enugu State

S/N	Group	No.	Mean	SD	DF	t.cal	t-value	Decision
1	INSTRUCTORS	30	3.01	0.78	298	1.56	1.96	Not significant
2	DISTANCE LEARNERS	270	3.07	0.87				

In the table above, the t-calculated value of each item was obtained; the degree of freedom of all items was 298, while the critical t-table of 1.96 was obtained at 0.05 level of significance. From the table, it can be seen that the t-calculated values for all items were less than critical t-value. Therefore, no significant difference between the mean ratings of distance learners and instructors on the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres in Enugu State was accepted.

3.2 Research Question Two

To what extent does personalized feedback through learning analytics enhance student engagement in distance learning centres in Enugu State?

Table 3: Mean ratings on extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State

S/N	ITEMS	Instructors			Learners		
		$\bar{X}$	SD	REM	$\bar{X}$	SD	REM
1	Individual Performance Feedback	2.81	0.89	A	3.19	0.95	A
2	Assignment-Specific Feedback	3.22	0.79	A	2.86	0.98	A
3	Quiz and Test Feedback	3.20	0.74	A	3.30	0.89	A
4	Timely Feedback	3.12	0.87	A	3.28	0.93	A
5	Progress-Based Feedback	2.17	0.77	DA	2.38	0.84	DA
6	Goal-Oriented Feedback	2.45	0.58	DA	2.14	0.73	DA
7	Weakness Identification Feedback	3.23	1.06	A	3.19	0.84	A
8	Strengths-Based Feedback	3.26	0.69	A	3.19	0.90	A
9	Corrective Feedback	3.21	0.71	A	3.31	0.74	A
10	Learning Resource Recommendation Feedback	3.35	0.72	A	3.36	0.77	A

X = Mean, SD = Standard Deviation, rem = Remark

The result in table 3 shows the mean responses and standard deviation of the respondents on the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State. The analysis on Table 3 shows that since the mean responses of items 5 and 6 are below the criterion mean of 2.50, the respondents disagreed that the items are extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State, while others with mean responses above 2.50 (criterion mean), indicate that respondents agree with them as the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State. The standard deviation of the items ranged from 0.58 to 1.06 indicating that the respondents were not too far from the mean and from one another in their response.

- **Ho_2:** There is no significant difference between the mean ratings of distance learners and instructors on the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State.

Table 4: t-test of the two groups on the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State

S/N	Group	No.	Mean	SD	DF	t.cal	t-value	Decision
1	INSTRUCTORS	30	3.04	0.78	298	1.70	1.96	Not significant
2	DISTANCE LEARNERS	270	3.05	0.84				

In the table above, the t-calculated value of each item was obtained; the degree of freedom of all items was 298, while the critical t-table of 1.96 was obtained at 0.05 level of significance. From the table, it can be seen that the t-calculated values for all items were less than critical t-value. Therefore, the null hypothesis of no significant difference between the mean ratings of distance learners and instructors on the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State was accepted.

3.3 Research Question Three

To what extent does early identification of student disengagement through learning analytics enhance student engagement in distance learning centres in Enugu State?

Table 5: Mean ratings on extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State

S/N	ITEMS	Instructors			Learners		
		$\bar{X}$	SD	REM	$\bar{X}$	SD	REM
1	Declining LMS Login Frequency	2.77	0.97	**A**	3.14	0.93	**A**
2	Reduced Course Material Access	3.14	0.83	**A**	2.81	1.08	**A**
3	Missed Assignment Deadlines	3.17	0.73	**A**	3.25	0.88	**A**
4	Low Participation in Online Discussions	3.09	0.86	**A**	3.23	0.92	**A**
5	Declining Quiz and Test Participation	2.72	0.92	**A**	3.09	0.98	**A**
6	Reduced Video Lecture Viewing	3.19	0.78	**A**	2.86	1.03	**A**
7	Decreased Time Spent on Learning Activities	3.20	1.05	**A**	3.19	0.84	**A**
8	Poor or Declining Academic Performance	3.28	0.68	**A**	3.13	0.95	**A**
9	Reduced Interaction with Tutors and Peers	3.17	0.69	**A**	3.31	0.74	**A**
10	Failure to Complete Course Activities	3.32	0.69	**A**	3.24	0.76	**A**

X = Mean, SD = Standard Deviation, rem = Remark

Table 5 shows the mean responses and standard deviations of the responses on extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State. The analysis on Table 5 shows that all the items have mean scores above the criterion mean of 2.50. This shows that the responses indicate that all the items are the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State. The standard deviation of the items ranges from 0.68 – 1.08, which indicates that the respondents were not too far from each other and from the mean in their responses.

Ho_3: There is no significant difference between the mean ratings of distance learners and instructors on the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State.

Table 6: t-test of the two groups on the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State

S/N	Group	No.	Mean	SD	DF	t.cal	t-value	Decision
1	INSTRUCTORS	30	3.14	0.79	298	1.43	1.96	Not significant
2	DISTANCE LEARNERS	270	3.17	0.88				

In the table above, the t-calculated value of each item was obtained; the degree of freedom of all items was 298, while the critical t-table of 1.96 was obtained at 0.05 level of significance. From the table, it can be seen that the t-calculated values for all items were less than critical t-value. Therefore, the null hypothesis of no significant difference between the mean ratings of distance learners and instructors on the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State was accepted.

4 DISCUSSION OF FINDINGS

The result with respect to research question one and hypothesis one shows that both instructors and distance learners share or have a similar view on the extent to which learning activity monitoring through learning analytics enhances student engagement in distance learning centres. They agreed that learning activity monitoring through learning analytics enhances: Student Attendance Monitoring, Student Login and Platform Access Monitoring, Assignment Submission Monitoring, Online Quiz and Test Participation Monitoring, Learning Material Access Monitoring, Time-on-Task Monitoring, Student–Tutor Interaction Monitoring and Course Progress and Completion Monitoring. These findings are in line with the statement credited to Munawar (2021) that learning activity monitoring is the regular observation of students' activities within an e-learning system, particularly their attendance, assignment submission,

and participation in quizzes, to track their learning progress. The findings are also in consonance with the statement credited to Matsumoto et al. (2025), that learning activity monitoring is the analysis and visualization of students' learning activity records, such as class participation and assignment submission, to identify students whose level of activity may require early support.

The findings with respect to research question two and hypothesis two shows that both instructors and distance learners have similar view on the the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres in Enugu State. They agreed that the extent to which personalized feedback through learning analytics enhances student engagement in distance learning centres include: Individual Performance Feedback, Assignment-Specific Feedback, Quiz and Test Feedback, Timely Feedback, Weakness Identification Feedback, Strenths-Based Feedback, Corrective Feedback and Learning Resource Recommendation Feedback. These findings are in concord with explanation made by Tetzlaff, Schmiedek and Brod (2021), that personalized instruction is the adjustment of teaching to the characteristics of an individual learner. Therefore, personalized feedback can be understood as feedback tailored to a learner's specific needs, characteristics and learning performance. The findings are also in line with the statement credited to Lim et al. (2020) that, personalized feedback in learning analytics is feedback provided to students based on their individual learning activities and behavioural data, with the aim of helping them understand their learning and improve their self-regulated learning processes.

The findings with respect to research question three and hypothesis three shows that both instructors and distance learners have similar view on extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State. They agreed that the extent to which early identification of student disengagement through learning analytics enhances student engagement in distance learning centres in Enugu State include: Declining LMS Login Frequency, Reduced Course Material Access, Missed Assignment Deadlines, Low Participation in Online Discussions, Declining Quiz and Test Participation, Reduced Video Lecture Viewing, Decreased Time Spent on Learning Activities, Poor or Declining Academic Performance, Reduced Interaction with Tutors and Peers and Failure to Complete Course Activities. The findings are in harmony with the statement credited to Atif et al. (2020), that early identification of disengagement as the timely use of learning-management-system data to identify students who may be at risk and require academic support or intervention. The findings are also in accord with the statement credited to Linden, van der Ploeg and Roman (2023) that, early identification of disengaged students as the use of explainable learning analytics to detect students showing early signs of reduced participation, such as failure to access the LMS or submit an early assessment.

5 CONCLUSION

Learning analytics represents an important opportunity for improving student engagement in distance education. Distance learning centres generate substantial quantities of information through learning-management systems and other digital technologies. When appropriately collected, analysed and interpreted, this information can help lecturers understand students' learning activities, provide personalized feedback and identify possible disengagement at an early stage. The study focused on three major applications of learning analytics: learning activity monitoring, personalized feedback and early identification of disengagement. The literature indicates that these applications have potential to support student engagement and academic success. However, analytics should not be regarded as a substitute for human interaction. Digital traces can reveal important aspects of student behaviour but cannot completely capture cognitive, emotional and social engagement. The responsible use of learning analytics also requires attention to privacy, transparency and trust. Students should understand how their information is collected and used. Learners have legitimate concerns about privacy and institutional use of educational data. For distance learning centres in Enugu State, the most useful approach is therefore one that combines analytics with human-centred educational support. Analytics can identify patterns, but lecturers and student-support personnel must interpret those patterns and respond appropriately.

Ultimately, learning analytics should be used not simply to monitor students but to understand, support and engage them. When combined with personalized feedback, early intervention, lecturer support and responsible data-governance practices, learning analytics can contribute to a more responsive and learner-centred distance education system.

Recommendations

The following recommendations were made based on the findings of this study:

- Distance learning centres should establish learning-analytics systems capable of monitoring students' academic participation, resource access, assessment activities and other relevant learning behaviours.
- Learning-analytics dashboards should be made available to lecturers and academic advisers so that they can identify students requiring academic support.

- Personalized feedback should be strengthened by using assessment and participation data to provide students with specific information about their academic progress.
- Early-warning mechanisms should be established to identify students whose engagement is declining. Such alerts should lead to supportive intervention rather than punitive action.
- Distance-learning lecturers should receive training in learning analytics. Training should cover data interpretation, dashboard use, student engagement, intervention strategies and ethical data management.
- Distance-learning centres should periodically evaluate their analytics systems to determine whether they improve participation, persistence and learning outcomes.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors report no conflict of interest. The authors alone are responsible for the content and writing of the paper.

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