Learning Analytics as a Tool for Closing the Assessment Loop in Business Education Programme in Universities in Edo State, Nigeria

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Abstract
The major purpose of this study was to determine the influence of learning analytics as a tool for closing the assessment loop in business education programme in universities in Edo state, Nigeria. The study adopted descriptive survey research design and was carried out in the universities in Edo State, Nigeria. The population for the study was 17 Business Education lecturers and 257 final year students of Business Education in Ambrose Alli University, Igbenedion University, and University of Benin. A structured 48 items questionnaire was used for data collection. The questionnaire was face-validated by three experts and was structured on a four-point scale of strongly agree, agree, disagree, and strongly disagree with values of 4, 3, 2, and 1 respectively. The internal consistency of the items of the questionnaire was ascertained through Cronbach Alpha technique which yielded a coefficient of 0.88 considered high enough for the study. The data collected were analyzed using mean ($\overline{X}$) and standard deviation to answer the research questions and t-test statistics to test the hypotheses. The study concluded that the adoption of learning analytics has the significance of closing the assessment loop in business education programme in universities. It was recommended amongst others that Business Education programme at all level of higher education should utilize learning analytics to close the assessment loop in business education programme.
Key words: Learning Analytics; Assessment Loop; Business Education Programme

Introduction

In the last few years, research in the field of learning analytics (LA) has been growing steadily. According to Siemens (2010), LA is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs. Building on ideas from process mining, data

processing, information retrieval, technology-enhanced learning, educational data mining, and visualization, LA is a multi-disciplinary research field that now forms its own domain (SoLAR, 2014). Learning analytics involves the collection and analysis of data to predict and improve student success.

There are vast amounts of data that Business Education programme can make use of to help predict and improve students' performance. There are a multitude of factors that have motivated interest in learning analytics. One motivating factor for the increased interest in learning analytics is the general trend for increased accountability in all levels of education. Educational institutions around Nigeria are increasingly pressured to account for what and how their students are learning. The pressure is even greater on online learning as these courses now have separate standards for accreditation (Ice, Swan, Burgess, Sharkey, Sherrill, Huston, & Okimoto, 2012). Learning analytics provides one of many methods which document student's performance as well as provides tools that encourage the continuous improvement needed by accrediting bodies. Institutions of higher education are experiencing greater demands to retain students; learning analytics has the goal to provide a more personalized learning experience through the use of data to respond to students' needs (Smith, Lange, & Huston, 2012). These kinds of personalization will likely lead to greater success in the classroom.

In addition to these national-level interests in learning analytics, there are more local goals that learning analytics address. These include predicting learner performance, suggesting to learners relevant learning resources, increased reflection and awareness on the part of the learner, detection of undesirable learning behaviors, and detecting affective states (boredom, frustration) of the learner (Verbert, Manouselis, Drachsler, & Duval, 2012).

Making use of learning analytics can give added value to business students as well as educators. Many Business Education courses today consist of a blended approach between classroom lectures and self-regulated learning activities. LA can help learners to better plan and reflect these activities by becoming aware of their actions and learning processes. Being aware of one's own situation is a three level process and a prerequisite for making decisions and effectively performing tasks: the perception of elements in the current situation is followed by the comprehension of the current situation which then leads to the projection of a future status. Govaerts, Verbert, Duval and Pardo (2012) observed that once learners are aware of their learning situation, they reflect on the phenomenon before them, and on the prior understandings which have been implicit in their behaviour would be engaged in a process of continuous learning. Reflection can promote insight about something that previously went unnoticed (Bolton, 2010) and lead to a change in learning behaviour. Thus, results of LA can be used to foster awareness and reflection (Verpoorten, Westera, & Specht, 2011; Verpoorten, 2012; Govaerts, Verbert, Duval, & Pardo, 2012) or to give recommendations for further steps in a current learning scenario (Greller & Drachsler, 2012). As Ferguson (2014) explains, LA offers ways for learners to improve and develop while a course is in progress. The author further stated that these analytics do not focus on things that are easy to measure. Instead, they support the development of crucial skills: reflection, collaboration, linking ideas and writing clearly. Awareness and reflection support for students are consequently highly important aims of learning analytics.

The various reasons for wanting to use learning analytics include improving

student success, increasing retention, and improving accountability. Long and Siemens (2011) describe a multitude of benefits of using learning analytics for higher education. Several of these benefits are focused on an administrative level, such as improving decision-making and informing resource allocation, highlighting an institution's successes and challenges, and increasing organizational productivity. Learning analytics can help business education programme identify at-risk learners and provide interventions, transform pedagogical approaches, and help students gain insight into their own learning. Having data at hand and knowing what to do with it can allow the programme realize these benefits. For example, if the programme learns (from a corelational analysis) that student performance on certain activities are not related to final grades, then the department might consider modifying these activities. Similarly, Business Education programme can use data from previous student's assessment to build a model of successful student behaviors, which might include the frequency of using learning analytic tool, frequency of accessing discussion board posts, and the number of times quizzes are taken. If Business Education programme can build a model of successful student behaviors, then the programme can encourage (with data) the students to engage in these behaviors. Alternatively, the programme can also identify at-risk students as ones who deviate from this model.

Likewise, Greller and Drachsler (2012) suggested that learning analytics can help Business Education programme by informing them of the gaps in knowledge displayed by their students. Understanding these knowledge gaps can help programme focus their attention on particular students or pieces of information. In order to support students within a course, teachers should be aware of what the students are doing, how they are interacting with the course material, where comprehension problems arise (Scheffel, Niemann, Leony, Pardo, Schmitz, Wolpers, & Kloos, 2012). Especially if the number of students in a course is high and the tasks the students are engaged in are not trivial, teachers need assistance for keeping track of the students' activities, for instance, with the help of activity-based learner-models (Florian, Glahn, Drachsler, Specht, & Fabregat, 2011).

There are some educational institutions that successfully use analytics to improve teaching, learning, and student success. Campbell, DeBlois, and Oblinger (2007) highlighted the institutions that have achieved success by making use of various types of data to predict student success. For example, the University of Alabama used data files from first-year students to be able to develop a model of retention based on various indicators such as business communication course grade and total hours earned. Sinclair Community College developed their Student Success Plan (SSP) for advising and retention. Collection and analysis of these data allowed them to track students and improve student success. In addition to these cases, there has also been success with making use of large data bases to understand student performance, with the goal of predicting success. For example, Verbert, Manouselis, Drachsler, and Duval (2012) describe various large educational datasets (dataTEL, DataShop, Mulce) that have been or can be used for learning analytic projects. Business Education programme in Nigerian universities can utilize these learning technologies tools to improve student's performances in both theory and practical base courses.

Learning analytics can be used at various levels, including the course, curriculum, institutional, and national level. La has the tendency of providing information that can be leveraged upon by Business

Education programme at all of these levels (Dringus, 2012). Learning analytics can be used to help students succeed and to improve retention. By collecting, analyzing, and predicting students' data, LA provides insights on the progress of the learner in real-time. Armed with this information, Business Education lecturers can make suggestions to students that will help them succeed (Long & Siemens, 2011). For example, if a student has not read instructions posted for a certain period of time, this may suggest to an instructor that the student needs an intervention or a push. Similarly, if a typically successful student suddenly performs poorly on an assignment, the instructor can intervene and seek to determine why the student performed poorly.

Despite the benefits presented by LA, there are a number of issues and concerns that should be highlighted in any discussion of learning analytics. At the forefront of these issues is the role of pedagogy in data analytics. It seems clear that the pedagogy should drive learning analytics and not necessarily the converse (Greller & Drachsler, 2012). This is challenging in that the instructor must from the beginning collects data of the students in order to make relevant predictions; this is even more cumbersome in a large class- like it is in most Business Education classes in Nigeria. Other issues that are frequently highlighted in discussions of learning analytics include profiling and how learning-analytics data to be used. Specifically, there is a danger of creating a profile of successful and unsuccessful students. More importantly, there is concern that a profile creates a set of expectations for the student and the programme at large (Campbell, DeBlois, & Oblinger, 2007). Of course, Business Education programme and its students already have expectations such as inculcating knowledge, skills and aptitude within the time frame as stipulated by the institutions; however, the issue is that learning analytics might add a set of data-driven expectations, which is problematic to manage. Data privacy and the use of data are also strong concerns of the use of learning analytics.

There are legal and ethical issues that need to be addressed before faculty or institutions can make use of some student data (Greller & Drachsler, 2012). Similarly, there is the issue of who the data belong to. Once the data have been warehoused, Campbell et al., (2007) questioned the possibility of anyone to have access to it. Also, there is the issue of whether or not we are really measuring student learning, or are we just attempting to boost student retention and course completion (Caldwell, 2012). If one considers the types of data that are mined for learning analytics, such as the number of course tools accessed in a learning situation, or the number of posts "read" on the discussion forum, are these really proxies for learning? This is not to suggest that learning analytics cannot boost learning, but there is need to be clear about what the programme is measuring and predicting. Ironically, Business Education programme has, for the most part, relied on their intuition and hunches to know when students are struggling, or to know when to suggest relevant learning resources, or to know how to encourage students to reflect on their learning. These intuition and hunches are not going to disappear with the advent of learning analytics, nor are the actions derived from them. Instead, learning analytics promises to make these hunches and the resulting action more data-driven and easier to detect, hence, the essence of this study.

Purpose of the Study

The major purpose of this study was to determine the influence of learning analytics as a tool for closing the assessment loop in business education programme in universities in Edo state, Nigeria.

Specifically, the study sought to determine the:

1. Significance of learning analytics in closing the assessment loop in business education programme in universities
2. Ways learning analytics can be utilized in closing the assessment loop in business education programme in universities
3. Challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities

Research questions

The following research questions guided the study:

1. What are the significance of learning analytics in closing the assessment loop in business education programme in universities
2. What are the ways learning analytics can be utilized in closing the assessment loop in business education programme in universities
3. What are the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities

Hypotheses

The following hypotheses guided the study and will be tested at 0.05 level of significance:

Ho_1 There is no significant difference between the mean responses of lecturers and students on the significance of learning analytics in closing the assessment loop in business education programme in universities

Ho_2 There is no significant difference between the mean responses of lecturers and students on the ways learning analytics can be utilized in closing the assessment loop in business education programme in universities

Ho_3 There is no significant difference between the mean responses of lecturers and students on the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities

Methodology

This study adopted descriptive survey research design and was carried out in the universities in Edo State, Nigeria. The population for the study was 17 Business lecturers and 257 final year students of Business Education in University of Benin, Ambrose Alli University, and Igbenedion University. The entire population was studied due to its manageable size. A structured 48 items questionnaire was used for data collection. The questionnaire was face-validated by three experts and was structured on a four-point scale of strongly agree, agree, disagree, and strongly disagree with values of 4, 3, 2, and 1 respectively. The internal consistency of the questionnaire was ascertained through Cronbach Alpha technique which yielded coefficients of 0.72, 0.84, and 0.86 for research questions 1, 2, and 3 respectively. However, the overall reliability yielded a coefficient of 0.88 which was high enough for the study. The data collected were analyzed using mean ($\overline{X}$) and standard deviation to answer the research questions, while t-test statistic was used to test the hypotheses. The real limit of numbers was used for interpreting the analysed data as follows: Strongly Agree: 3.50 – 4.00, Agree: 2.50 – 3.49, Disagree: 1.50 – 2.49, and Strongly Disagree: 0.50 – 1.49. In the test of hypotheses, a hypothesis of no significant difference was accepted when the probability (p) value is greater than or equal to .05 otherwise, it was rejected.

Results

Table 1

Mean, Standard Deviation and T-test results of respondents on the significance of learning analytics in closing the assessment loop in business education programme in universities

N= 274

S/N	Items Statement	1 $\bar{X}$	2 SD	3 Rk	4 $\bar{X}_1$	SD_1	5 $\bar{X}_2$	SD_2	6 P-value
					Lecturers		Students		
1.	Provides information to the department on the gaps in knowledge displayed by the students	2.83	1.07	A	2.82	1.04	2.84	1.09	.83+
2.	Improves accountability in teaching and learning of business courses	3.23	.77	A	3.20	.79	3.25	.75	.45+
3.	improving decision-making and informing resource allocation	3.23	.90	A	3.26	.92	3.19	.88	.35+
4.	assist the department in identifying at-risk learners and provide interventions	2.89	.90	A	2.82	.93	2.98	.86	.03*
5.	it transform pedagogical approaches,	3.32	.77	A	3.26	.82	3.39	.70	.04*
6.	helps students gain insight into their own learning	2.67	.93	A	2.64	.88	2.71	.97	.36+
7.	it helps the students in linking ideas and writing clearly	3.08	.86	A	3.01	.80	3.15	.93	.05+
8.	predicting learner performance	3.04	.86	A	2.94	.88	3.14	.84	.01*
9.	utilization of data to respond to students' needs	2.75	1.00	A	2.59	.95	2.92	1.04	.00*
10.	provides a more personalized learning experience	3.07	.94	A	3.01	.96	3.15	.91	.07+
11.	It helps the teacher to be aware of where comprehension problems arise	2.99	.95	A	2.91	.98	3.07	.91	.05+
12.	It helps the teacher to be aware of how they are interacting with the course material	2.52	1.01	A	2.43	1.02	2.62	.99	.02*
13.	It helps the teacher to be aware of what the students are doing	2.89	.92	A	2.86	.94	2.93	.89	.30+
14.	suggesting to learners relevant learning resources	2.97	.80	A	2.94	.81	3.01	.79	.26+
15.	support the development of crucial skills	3.07	.90	A	3.06	.92	3.07	.88	.92+
16.	gives recommendations for further steps in a current learning scenario	3.14	.93	A	3.09	.92	3.20	.94	.17+
17.	engages the students in a process of continuous learning	2.67	1.03	A	2.62	1.06	2.73	1.00	.21+
18.	creating awareness on student's actions and learning processes	2.76	1.05	A	2.74	1.05	2.77	1.05	.69+
19.	help learners to better plan and reflect academic activities	2.81	1.07	A	2.73	1.12	2.90	1.02	.05+
20	detecting affective states (boredom, frustration) of the learner	3.12	.78	A	3.12	.80	3.10	.75	.83+
21	increased reflection and awareness on the part of the learner	3.01	.93	A	2.97	.97	3.08	.81	.33+
22	detection of undesirable learning behaviors	2.79	.88	A	2.91	.92	2.53	.74	.00*

Key: $\bar{X}$ & SD= Mean & Standard Deviation of the two groups of respondents; X_1= *Mean of* Lecturers*;* ***X_2 =*** *Mean of Students;* ***SD_1=*** *Standard Deviation of Lecturers;* ***SD_2=*** *Standard Deviation of Students;* ***DF=*** *degree of freedom= 273;* ***Sig=*** *probability value;* ***RK= Remarks****; A=Agree;* ******* *= significant; += Not Significant*

Table 1 presented the mean ratings and standard deviations of respondents on the significance of learning analytics in closing the assessment loop in business education programme in universities. The data in column 1 revealed that items 1 - 22 had mean ratings ranging from 2.52 to 3.32, indicating that the respondents agreed that the items are significance of learning analytics in closing the assessment loop in business education programme in universities. The standard deviations in column 2 ranged from 0.77 to 1.07 which were less than 1.96. This implies that the respondents were not far from each other in their opinions.

To test hypothesis one, independent t-test statistic was used and the data are presented in Table 1 (columns 4 to 6). The data in column 6 indicated that items 4, 5, 8, 9, 12 and 20-21 had probability values ranging from .00 to .04 which were less than .05. Therefore, the hypothesis of no significant difference for these items was rejected. On the other hand, hypothesis of no significant difference for items 1-3, 6, 7, 10, 11, 13-19 and 22 with probability values ranging from .05 to .92 were upheld. This indicated that both Lecturers and students did not differ significantly on these items which determine the significance of learning analytics in closing the assessment loop in business education programme in universities.

Table 2

Mean Ratings, Standard Deviations and t-test Analysis of the Responses of lecturers and students on the ways learning analytics can be utilized in closing the assessment loop in business education programme in universities

S/N	Items Statement	1 $\overline{X}$	2 SD	3 Rk	4 $\overline{X}_1$	SD_1	5 $\overline{X}_2$	SD_2	6 P-value
					Lecturers		Students		
23	Monitoring individual student performance	2.83	1.07	A	2.82	1.04	2.84	1.09	.83+
24.	Extracting both positive and negative data from students performance	3.23	.77	A	3.20	.79	3.25	.75	.45+
25.	automatic response to students triggers	3.23	.90	A	3.26	.92	3.19	.88	.35+
26.	utilize what-if decision support	2.89	.90	A	2.82	.93	2.98	.86	.03*
27.	Disaggregating student performance by selected characteristics such as major, year of study, ethnicity	3.32	.77	A	3.26	.82	3.39	.70	.04*
28.	Identifying outliers for early intervention	2.67	.93	A	2.64	.88	2.71	.97	.36+
29.	instructional techniques	3.08	.86	A	3.01	.80	3.15	.93	.05+
30.	Identifying and developing effective	3.04	.86	A	2.94	.88	3.14	.84	.01*
31.	Predicting potential to enable all students achieve optimally	2.75	1.00	A	2.59	.95	2.92	1.04	.00*
32.	Preventing attrition from a course or program	3.07	.94	A	3.01	.96	3.15	.91	.07+
33.	mining the type of data necessary for assessing students performance	2.99	.95	A	2.91	.98	3.07	.91	.05+
34.	predictive modeling of evaluating contents	2.52	1.01	A	2.43	1.02	2.62	.99	.02*
35.	Analyzing standard assessment techniques and instruments	2.89	.92	A	2.86	.94	2.93	.89	.30+
36.	Testing and evaluation of curricula	2.97	.80	A	2.94	.81	3.01	.79	.26+

Table 2 (columns 1 and 2) presented the mean ratings and standard deviations of respondents on the ways learning analytics can be utilized in closing the assessment loop in business education programme in universities. The data in column 1 revealed that items 23 - 36 had mean ratings ranging from 2.52 to 3.32, indicating that the respondents agreed that these items are ways learning analytics can be utilized in closing the assessment loop in

business education programme in universities. The standard deviations in column 2 ranged from 0.77 to 1.07 which were less than 1.96. This implies that the respondents were not far from each other in their opinions.

To test hypothesis two, the data in Table 2 (columns 4 to 6) was used. The data in column 6 indicated that items 26-27, 30 and 34 had profitability values that ranged from 0.00 to .04 which were less than .05. This means that there is a significant difference in the responses of on lecturers and students on these items measuring ways learning analytics can be utilized in closing the assessment loop in business education programme in universities. As such, the hypothesis of no significant difference for these items was rejected. On the other hand, hypothesis of no significant difference for items 23-25, 28-29,31-33 and 35-36 with probability values ranging from .05 to .92 were upheld. This indicated that both lecturers and students do not differ significantly in their opinion on these items measuring ways learning analytics can be utilized in closing the assessment loop in business education programme in universities.

Table 3

Mean Ratings, Standard Deviation and t-test Analysis of the Responses of lecturers and students on the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities

		1	2	3	4		5		6
S/N	Items Statement	$\overline{X}$	SD	Rk	$\overline{X}_1$	SD_1	$\overline{X}_2$	SD_2	P-value
					Lecturers		Students		
37.	Threat to some students to know that someone can see and track all that they do	2.97	.81	A	2.96	.84	2.97	.75	.95+
38.	There is a concern that any data set, no matter how comprehensive, cannot take in to account other issues, such as interpersonal ones	2.81	.91	A	2.82	.93	2.79	.88	.74+
39.	There is the issue of whether or not learning analytics are really measuring student learning, or boosting student retention and course completion	3.28	.77	A	3.29	.77	3.27	.77	.82+
40.	No institutional backing on the need to adopt learning analytics	2.58	1.07	A	2.62	1.08	2.50	1.05	.38+
41	There are still very few software programs and teaching materials available learning analytics to take place	2.97	.70	A	2.99	.72	2.93	.65	.50+
42.	Difficulty in profiling how learning-analytics data will be used in teaching business education courses	3.12	.78	A	3.12	.80	3.10	.75	.83+
43.	Learning analytic is faced with the danger of creating a profile of successful and unsuccessful students	3.01	.93	A	2.97	.97	3.08	.81	.33+
44.	Difficulty in acquiring learning analytic tools due to its expensive nature	2.79	.88	A	2.91	.92	2.53	.74	.00*
45.	Data privacy and the use of data are also strong concerns of the use of learning analytics	2.99	.83	A	3.04	.87	2.88	.74	.11+
46.	Inability to address legal and ethical issues in learning analytics making use of a student data	2.98	.90	A	2.91	.93	3.12	.79	.06+
47.	There is the issue of who the data belong to once the data have been warehoused	2.85	1.01	A	2.97	1.01	2.59	.97	.00*
48.	Difficulty to persuade teachers to modify their instructional design to suit learning analytics	2.57	.92	A	2.64	.99	2.40	.70	.03*

Table 3 presented the mean ratings and standard deviations of lecturers and students on the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities. The data in column 1 revealed that items 37 – 48 had mean ratings ranging from 2.57-3.28. The implication of this is that the respondents agreed in their opinions that those items are challenges in utilizing learning analytics in closing the assessment loop in business education programme in universities. The standard deviations in column 2 ranged from 0.70 to 1.07 and were below 1.96. This showed that the respondents were not far from the mean and from each other in their opinions.

To test hypothesis three, independent t-test statistic was used and the data are presented in Table 3 (columns 4 to 6). The data in column 6 revealed that items 44 and 47-48 had probability values that ranged from 0.00 to 0.03, which were less than 0.05 thus, hypothesis of no significant difference for these items was rejected.. However, hypothesis of no significant difference for items 37-43 and 45-46 with probability values that ranged from 0.06 to 0.95 were accepted, indicating that both lecturers and students do not differ significantly in their opinion on these items measuring the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities.

Discussion of Findings

The findings on the significance of learning analytics in closing the assessment loop in business education programme in universities revealed that there are many benefits to learning analytics; most notably is that it can provide information on how to help students succeed. In educational institutions, there are enormous amount of data at the disposal of the administrators and lecturers. The ability to harness this data and use it to inform teaching and learning activities in the classroom, whether face-to-face or online, is at the heart of learning analytics. As indicated in the findings, Business Education programme can make use of the data available from the learning analytics tools in various courses to affect change in students' assessment issues and improve student success. These efforts can have a large impact on student success. Learning analytics also offers the promise of more personalized learning, which enables students to have more effective learning experiences, among other things. This finding is in line with Greller and Drachsler (2012) who stated that personalized learning experience is important in overcoming the assumption and practice of many course designers that learners start the course at the same stage and proceed through it at roughly the same pace; what Siemens refers to as the efficient learning hypothesis (Siemens, 2010). Without the use of performance and learning data, instructional designers are pigeon-holed into accepting this hypothesis. The use of data that is automatically collected by most teachers would allow business education programme to shape how students proceed through a course. Supporting this finding also is Smith, Lange and Huston (2012) who found that the frequency with which students log in to their personal assessment data, how often they engaged in the material, their pace, and assignment grades successfully predicted their performance in the course. Just as Amazon.com used the data from their purchase history to make suggestions about future purchases (Campbell, DeBlois, & Oblinger, 2007), so can learning analytics allow teachers to suggest new learning opportunities or different courses of action to the students.

The findings on hypothesis one indicated that both Lecturers and students did not differ significantly on the significance of learning analytics in closing the assessment loop in business education programme in universities. The implication of this finding is that both the students and lecturers in business education are willing to embrace the benefits presented by learning analytics in solving the assessment difficulties usually experienced in teaching and learning of business education courses.

The findings on the ways learning analytics can be utilized in closing the assessment loop in business education programme in universities revealed that monitoring individual student performance; disaggregating student performance by selected characteristics such as major, year of study, ethnicity, etc.; identifying outliers for early intervention; predicting potential so that all students achieve optimally; preventing attrition from a course or program; identifying and developing effective instructional techniques; analyzing standard assessment techniques and instruments testing and evaluation of curricula are ways in which learning analytics can be utilized to improve student achievement in Business Education programme. It was found that each of these ways are amenable to learning analytics and can generally be accomplished by gathering data from an instructor records. In addition, being able to mine the type of data necessary to achieve these goals will go far in helping to improve student success and increase retention as doing so is likely to optimize student learning experiences. Olmos and Corrin (2012), and May (2011) in line with these findings, posited that learning analytics can be both descriptive and predictive. This approach is also consistent with the five stages of the use of learning analytics in higher education as suggested by Goldstein and Katz (2005): data extraction, performance analysis, what-if decision support, predictive modeling, and automatic response triggers. Consistent with the goals of school assessment, learning analytics can help Business Education programme improve teaching and learning opportunities for both teachers and students. By monitoring student performance and participation in a course, as well as examining how this relates to grades, Business Education programme can potentially spot areas of the course to improve. Such improvements in the course allow for the continual improvements that accrediting bodies are recommending.

The finding on hypothesis two showed that both business education lecturers and students do not differ in their opinion on the ways learning analytics can be utilized in closing the assessment loop in business education programme in universities. Their agreement implies that learning analytics can be utilized both as a descriptive and predictive tools for learning in a business education classroom. From a descriptive perspective, learning analytics can help in answering such questions as: what happened, where was the problem, and what actions are needed? Learning analytics can also help both teachers and students to predict and prescribe situations by answering such questions as: why are these happening, what if these trends continue, what will happen next, and what is the best that can happen? Thus, this tool is timely for adoption.

Furthermore, the findings on the challenges to utilizing learning analytics for closing the assessment loop in business education programme in universities revealed that learning analytics may be threatening to some students and lecturers to know that someone can monitor and track all that they do during the teaching learning process, which may lead to distrust. There is also a concern that any data set, no matter how comprehensive, cannot take into account other issues, such as interpersonal ones. Furthermore, the department or heads of

programme need to be involved in order for learning analytics to have its greatest impact as the department and institutions are obligated to use data to increase the probability of student success. It was further revealed that the existence and impact of learning analytics goals, are however, hard to measure due to the lack of standards that the student support of LA tools can be measured against. These findings support Campbell et al. (2007) and Dringus (2012) who argued that learning analytics (in online courses), must get meaningful data, have transparency, yield good algorithms, lead to effective use of the data, and inform process and practice. Without attending to these minimal requirements, learning analytics can be harmful to the student's progress as inaccurate assessment data would have been employed by the instructor in assessing the performance of the student.

The finding on hypothesis three which states that there is no significant difference between the mean responses of lecturers and students on the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities revealed that both lecturers and students do not differ significantly in their opinion on these items measuring the challenges to utilizing learning analytics in closing the assessment loop in business education programme in universities. The implication is that both the lecturers and students accept to the fact that learning analytics, though of great significant in closing the assessment loop in business education come with numerous challenges which must be attended to, if learning analytics must be achieved.

Conclusion

The study was conducted to determine the influence of learning analytics as a tool for closing the assessment loop in business education programme in universities in Edo state, Nigeria. Based on the findings of the study, it was concluded that learning analytics is of great significance in closing the assessment loop in business education programme; as such, it must follow certain ways when being utilized in closing the assessment loop in business education programme in universities. Despite the benefits inherent in learning analytics, there are some challenges standing against the utilization of learning analytics in closing the assessment loop in business education programme in universities.

Recommendations

Based on the findings of the study, the following recommendations were made:

1. Business Education programme in all tertiary institution should ensure the utilization of learning analytics in closing the assessment loop in business education programme.
2. Business education lecturers should utilize learning analytics in identifying and developing effective instructional techniques to help *in* closing the assessment loop in business education programme.
3. Learning analytics should be adopted in Business education programme in analyzing standard assessment techniques and instruments testing for evaluation of business curriculum
4. In order to overcome the challenge of unwanted tracking, learning analytics tools should be passworded by an administrator.

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