Readiness for adoption of Learning Analytics to Support Technology-Enabled Learning in Universities in Kenya

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Abstract:- Many institutions are moving toward the adoption of virtual learning technologies. Learning analytics adoption is one of the rapidly growing technologies to report data left as digital footprints by students in E-learning environments so that the quality and value of their learning experience can be improved. The aim of this study was to evaluate readiness level for adoption of Learning Analytics to support Technology-enabled learning in universities in Kenya. The case study research design was used. Simple random sampling and purposive sampling techniques was used. The sample size for this study was 379 students while teaching staff were selected purposively This study used questionnaire as data collection tool from students and an interview schedule to collect opinion from teaching staff. The validity of the tool was tested using IT experts while the reliability was realized through use of Cronbach's alpha internal consistency coefficient. Findings from the data collected indicate that most respondents agreed that there is readiness on adapting Learning Analytics. This shows that Learning Analytics is usable, there's management support, availability of finances to support Learning Analytics adoption, and adequate system integration to give room for the adoption of learning analytics tools with the existing systems. Universities will benefit from enhanced market analysis, improved adapted learning environment, analyzed career consulting based on student data, minimize students' drop-out from classes and supported decision making.

Keywords:- *Technology-Enabled Learning, Virtual Learning Environment, Learning Analytics.*

I. INTRODUCTION

Higher education institutions globally are constantly embracing ICT as a learning tool (Kumpulainen, 2007). Ocak (2006) observed that higher education institutions are embracing the use of ICT in a variety of ways, including using e-learning as a method of delivery to react to the demand for improved access to their resources and therefore creating Virtual Learning Environments (VLEs).

Learning analytics, artificial intelligence in education, and educational data mining have all grown in tandem with the growing use of data and technology in education, with a particular focus on how data may be utilized to research and inform learning. There is interest in how data may inform learning across all stakeholders - at the institutional, departmental, and individual academic and student levels (Buckingham Shum, 2012). Major technology companies have taken notice of this interest, and are increasingly promoting analytics packages for their products, especially those based on Learning Management Systems (LMS).

Learning analytics (LA) is a technique to report data left as digital footprints by students in E-learning environments, such as their activity, participation, or reactions, so that the quality and value of their learning experience can be improved. Learning analytics is concerned with gaining a better knowledge of the learning and teaching process as well as interpreting student data in order to improve student success and learning outcomes (Czerkawski, 2015).

Learning analytics can be used to analyze data to identify any learning challenges, and it can potentially give a learner engagement model to enhance academic success in the learners' best interests (Arnold, 2012).Furthermore, through the lens of learning analytics, online learning tasks recorded on e-Learning platform can give evidence for competence assessment (Rayón, 2014). Learning metrics derived from students' learning activities can be used to identify learning patterns and measure parameters that might help with competency evaluation.

Learning Analytics can support the classic educational system helping teachers to analyze what students know and what techniques are most effective for each pupil. In this way, also teachers are able to learn new techniques and methods about their education work.

According to Broughan & Prinsloo (2019), most of the Learning Analytics educational researches have focused on learner's behavior and performances and to cater to learners' needs, the learning experience needs to be personalized. With online learning booming, we now have bigger data than ever before. Roberts et al. (2016) acknowledges that Learning Analytics can really improve the education, can afford to shape modern and dynamic education system, which every individual student can have the maximum benefit from that. Learning Analytics may assist teachers examine what students know and which strategies are most effective for each student, which can support the traditional educational system. Teachers can discover new approaches and procedures for their educational work in this way.

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The utilization of various Virtual Learning Environments mostly Learning Management System, for Technology-enabled learning in higher education has increased, yet there is limited data indicating an improvement in student learning outcomes (Phillips, et al., 2011). It is necessary to identify more precise methods of assessing the efficacy of Virtual Learning Environments that do not require instructor engagement. Learning Analytics has enabled a solution to this need, as it is capable of utilizing log data to gain insight into the learning activities that take place within the LMS platform (Jo, I.-H, Kim, & Yoon, 2014).

Although Learning Analytics have the potential to improve student performance, there is no evidence that Kenyan institutions have been using the tool. Many Learning Management Systems have student tracking capabilities, however they are generic and do not provide the data extraction and aggregation that could be beneficial for different contexts (Ferguson R. , 2012).

There is need for universities to interpret student experience using the data they generate on the learning management systems; this will help instruction be individualized for student needs and student performance can be predicted in future planning efforts. Furthermore, data generated as students interacts with the LMs can help predict their successes or failures in online courses (Farooq, Schank, Harris, Fusco, & Schlager, 2007).

Hence the purpose of this study is to evaluate level of readiness for adoption of learning analytics in Universities in Kenya

II. METHODOLOGY

This study used a case study research design. This helped in-depth understanding of the research problem. It also enhances existing knowledge while doing away with possible biasness. According Burawoy (2009) Case study research looks on a real-life phenomenon in depth and within the context of its surroundings. An individual, a group, an organization, an event, a problem, or an anomaly can all be examples of such cases.

The study was conducted using a five-point Likert scale questionnaire. Respondents were Kibabii University teaching staff and students from various courses and educational levels. The population for this study were students and teaching staff who are using VLE at the university during data collection period.

This study used purposive and simple random sampling techniques. When using random sampling, each member of the population had an equal chance of being chosen and this avoided biasness by offering equal representativeness of the sample (Rahim, 2008). Purposive sampling was used to select teaching staff having knowledge in online teaching and learning. The researcher used simple random sampling to select a group of students using Learning Management system in the university.

Sample Size was determined by calculation using Taro Yamane Formula (Yamane, 1973).

$$\boldsymbol{n = \frac{N}{1 + Ne^2}}$$

Where n = sample size
N = population size =**7112**
e = error (0.05) reliability level 95%
or; *e* = level of precision always set the value of 0.05
Population Size=Active Students (7112)
Source: (Kibabii University Admissions Office as at August 2022)

$$n = \frac{7112}{1+7112(0.05)^2} \quad =379$$

III. DATA ANALYSIS AND FINDINGS

This chapter presents analysis of the data collected using a questionnaire from randomly selected 288 respondents who includes teaching staff and students of Kibabii University.

➢ *Response Rate*

A response of 288 (74.06%) dully filled questionnaire was obtained out of the expected 389 sampled respondents. According to Fox (2020), 60% response rate is strong - and meets an acceptable standard, thus the rate of response indicted a reasonable sample for analysis.

➢ *Demographic Information*

- *Response rate and Category*

The findings are as shown in Table 1: Respondent category below;

Table 1: Respondent category

	Frequency	Percent
Academic Staff	3	1.05
Student	285	98.95
Total	288	100.0

From Table 1: Respondent category, Majority of the respondents accounting to 98.95% which add up to 285 respondents were Students while 1.05% which adds up to 3 of the respondents were Academic staff. In relation with the sample frame, a sample size of 386 students and 3 academic staff was required for this study.

➢ *Experience of Technology-enabled learning use*

The study collected data on experience of the respondents on the use of technology-enabled learning. The findings are presented in Table 2.

Table 2: Years of experience on the use of technology-enabled learning

	Frequency	Percent
Less than a year	55	19.1
1-2 years	68	23.6
3 years and above	165	57.3
Total	288	100.0

Table 2 above categorizes respondents according to year they have experience with TEL within the university. Most of the respondent accounting to 57.3% have used TEL for three years and above, followed by 23.6% of the respondents who have 1-2 years' experience with TEL while 19.1% of the respondents have less than a year in using TEL in the university. This implies that majority of the respondents have three years on above in using technology for teaching and learning.

➢ *Importance of Learning Analytics in learning/teaching*

The study also collected data from respondents to rate how importance of Learning Analytics in learning/teaching. The rate was Very important, Slightly important, Not at all important and Not sure whether important or not important.

The findings are summarized in table 3: Importance of Learning Analytics in learning/teaching

Table 3: Importance of Learning Analytics in learning/teaching

	Frequency	Percent
Very important	214	74.3
Slightly important	26	9.0
Not at all important	8	2.8
Not sure whether important or not important	40	13.9
Total	288	100.0

Table 3 above shows that majority of the respondents 74.3% indicated that learning Analytics tool is very important while 13.9% were not sure whether the tool is important or not.

➢ *Suitability of Data for factor Analysis*

To determine whether the sampled data was appropriate for factor analysis, the researcher used the Bartlett's test of sphericity and the Kaiser-Meyer-Olkin measure of sampling adequacy. The table below, Table 4, describes the output.

Table 4: Readiness of adoption of learning analytics KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.944
Bartlett's Test of Sphericity	Approx. Chi-Square	8589.630
	df	210
	Sig.	.000

Based on Table 4 above, the Kaiser-Meyer-Olkin Measure of sampling adequacy value is 0.944, which is greater than 0.6, according to the readiness of adoption of learning analytics KMO and Bartlett's Test. Accordingly, it can be concluded that the underlying causes can account for 94% of the variability. In addition, Bartlett's test of sphericity's significant (p) value, which is less than 0.05, is 0.000. The data is scalable to be subjected to factor analysis if it has a KMO value greater than 0.6 and a significant Bartlett's test of Sphericity value.

➢ *Factor Extraction*

- *Satisfaction Construct*

In this study, four (4) indicators were given to responders to rate them on a Likert scale from Strongly Disagree (1), Disagree (2), Neither Agree nor Disagree (3), Agree (4) and to Strongly Agree (5) and were converted into Satisfaction Construct, as detailed in Table 5 Satisfaction Construct, requested the respondents to score their level of agrment with respect four (4) different indicators

Table 5: Satisfaction Construct

	N	Mean	Std. Deviation
My university intends to use a learning analytics tool in the near future.	288	3.93	1.119
I think Learning analytics will allows me to access more information about my courses	288	4.08	1.026
My university has recently started using learning analytics tool.	288	3.78	1.159
I have the knowledge necessary to use learning analytics.	288	3.65	1.276
Kendall's W[a]	.048		
Chi-Square	67.220		
df	3		
Asymp. Sig.	.000		
a. Kendall's Coefficient of Concordance			

Research findings with respect to Table 5: Satisfaction Construct shows that the highest mean ranked indicators were; 'I have the knowledge necessary to use learning analytics' with a mean value of 3.65; 'My university has recently started using learning analytics tool.' with a mean value of 3.78; 'My university intends to use a learning analytics tool in the near future' with a mean value of 3.98. The lowest mean ranked indicators was; 'I think Learning analytics will allow me to access more information about my courses' with a mean of 4.08.

The level of agreement within the indicators in the satisfaction construct was also rated using inferential data analysis. The degree of agreement among the respondents was evaluated using Kendall's correlational concordance technique. The null hypothesis (H0) that there is no statistically significant correlation between the satisfaction factors and satisfaction construct served as the foundation for this construct.

The findings in Table 5 demonstrate that the respondents' agreement has a weak concordance relationship of (Wa = 0. 048). With a degree of freedom (df) of 3, the Chi-Square value (X2) was 67.220. The investigation failed to support the null hypothesis (H0) that Feedback metrics and Feedback construct have no statistically relationship since the asymptotic significant value (p-value) was 0.033, which is less than (0.05). This suggests that the satisfaction indicators and the satisfaction construct have a statistically significant relationship.

- *Management support construct*

In this study, seven (7) indicators were converted into Management Support construct and were given to respondents in order to be rated on a Likert scale from Strongly Disagree (1), Disagree (2), Neither Agree nor Disagree (3), Agree (4) and to Strongly Agree (5) for Management Support Construct, as detailed in Table 6: Management support Construct, requested the respondents to score their level of agreement with respect six (6) different indicators

Table 6: Management support construct

	N	**Mean**	**Std. Deviation**
My institution has policies in place for the data used for learning analytics that sufficiently protect users from harm	288	3.73	1.183
My institution has policies in place for the data used for learning analytics that sufficiently protect faculty and students' privacy	288	3.82	1.101
My institution has a role or function responsible for overseeing learning analytics policy	288	3.86	1.078
My institution has a clearly articulated definition of equity and guidelines for how equity should be operationalized	288	3.93	1.077
Faculty have been notified and are aware of institutional policies and ethical considerations of the use of learning analytics	288	3.81	1.089
Stakeholders across my institution are included in the policy/guideline creation process	288	3.82	1.129
My institution has processes in place to evaluate learning analytics technology (whether developed in-house or through a vendor)	288	3.81	1.160
Kendall's W[a]	.019		
Chi-Square	32.992		
df	6		
Asymp. Sig.	.000		
a. Kendall's Coefficient of Concordance			

Research findings on Table 6 above shows that the highest mean ranked indicators were: 'My institution has policies in place for the data used for learning analytics that sufficiently protect users from harm' with a mean value of 3.73; 'Faculty have been notified and are aware of institutional policies and ethical considerations of the use of learning analytics.' and 'My institution has processes in place to evaluate learning analytics technology' both with a mean value of 3.81 respectively; 'Stakeholders across my institution are included in the policy/guideline creation process' with a mean value of 3.82 'My institution has a role or function responsible for overseeing learning analytics policy' had a mean value of3.86. The lowest mean ranked indicators was; 'My institution has a clearly articulated definition of equity and guidelines for how equity should be operationalized' with a mean of 3.93.

The level of agreement within the indicators in the " Management support " construct was also rated using inferential data analysis. The degree of agreement among the respondents was evaluated using Kendall's correlational concordance technique. The null hypothesis (H0) that there is no statistically significant correlation between the management support factors and management support construct served as the foundation for this construct.

According to Table 6, there is a weak concordance relationship between the respondents' agreement (Wa = 0.019). The Chi-Square value (X2) was 32.992 with a degree of freedom (df) of 6. Since the asymptotic significant value (p-value), which is less than (0.05), was 0.019, the investigation did not support the null hypothesis (H0), according to which there is no statistical relationship between management support metrics and management support construct. This implies that there is a statistically significant relationship between the management support construct and the management support indicators.

- *Cost construct*

In this study, six (6) indicators were converted into Cost construct and were given to respondents to rate them on a Likert scale from Strongly Disagree (1), Disagree (2), Neither Agree nor Disagree (3), Agree (4) and to Strongly Agree (5) for the Cost Construct, as detailed in Table 7 below, requested the respondents to score their level of agreement with respect six (6) indicators.

Table 7: Cost Construct

	N	Mean	Std. Deviation
My university have the resources necessary to use learning analytics	288	3.73	1.254
My institution has a role or function responsible for ensuring proper training and professional development for learning analytics	288	3.87	1.090
My institution has facilities for learning analytics training across role and function	288	3.78	1.208
My institution provides sufficient incentives to support the growth of learning analytics on campus	288	3.81	1.134
My institution has sufficient technical infrastructure to support data sharing & integration across systems	288	3.83	1.199
My institution has a role or function responsible for ensuring proper infrastructure and use of learning analytics technologies	288	3.89	1.113
Kendall's W^a	.011		
Chi-Square	15.635		
df	5		
Asymp. Sig.	.008		
a. Kendall's Coefficient of Concordance			

The findings on Table 7 above shows that the highest mean ranked indicators were 'My university have the resources necessary to use learning analytics' with a mean value of 3.73; 'My institution has facilities for learning analytics training across role and function' with a mean value of 3.78; 'My institution provides sufficient incentives to support the growth of learning analytics on campus' with a mean value of 3.81; followed by 'My institution has sufficient technical infrastructure to support data sharing & integration across systems' with the mean value of 3.83. The lowest mean ranked indicators were;' My institution has a role or function responsible for ensuring proper training and professional development for learning analytics' with a mean value of 3.87; and 'My institution has a role or function responsible for ensuring proper infrastructure and use of learning analytics technologies' with a mean value of 3.89;

A rating of the degree of agreement among the indicators in the "Cost" construct was also made using inferential data analysis. Using Kendall's correlational concordance method, the respondents' level of agreement was assessed. This construct was built on the null hypothesis (H0), according to which there is no statistically significant relationship between the factors that affect cost and cost construct.

The results in Table 7 above show a weak concordance relationship (Wa = 0.015) between the respondents' agreement and their opinions. The Chi-Square value (X2) with a degree of freedom (df) of 5 was 17.811. Given that the asymptotic significant value (p-value), which is less than (0.05), was 0.033, the study was unable to demonstrate that there is no statistical relationship between the cost metrics and the cost construct (H0). This implies that there is a statistically significant relationship between the cost construct and the Feedback indicators.

- *Integration construct*

In this study, four (4) different indicators were converted into Integration construct and were given to given to respondents to rate them on a scale from Strongly Disagree (1), Disagree (2), Neither Agree nor Disagree (3), Agree (4) and to Strongly Agree (5) for the integration Construct, as detailed in Table 8 integration Construct, requested the respondents to score their level of agreement with respect four (4) different indicators

Table 8: Integration Construct

	N	Mean	Std. Deviation
Learning analytics tools are compatible with other learning tools I use for teaching/learning	288	3.79	1.157
Faculty and administrators have access to disaggregated data that enables the assessment of equity gaps	288	3.78	1.127
Faculty have access to course-level data that allow them continuously improve teaching	288	3.90	1.063
My institution has processes in place to evaluate collected data to ensure data accuracy and applicability	288	3.92	1.154
Kendall's W^a	.013		
Chi-Square	11.094		
Df	3		
Asymp. Sig.	.011		
a. Kendall's Coefficient of Concordance			

Research findings with respect to Table 8: Integration Construct shows that the highest mean ranked indicators were 'Faculty and administrators have access to disaggregated data that enables the assessment of equity gaps' with a mean value of 3.78; 'Learning analytics tools are compatible with other learning tools I use for teaching/learning' with a mean value of 3.79; 'Faculty have access to course-level data that allow them continuously improve teaching' with a mean value of 3.90. The lowest mean ranked indicators was 'My institution has processes in place to evaluate collected data to ensure data accuracy and applicability' with a mean of 3.92.

Using inferential data analysis, the degree of agreement among the indicators in the "Integration" construct was also evaluated. The Kendall correlational concordance method was used to assess the respondents' level of agreement. The foundation for this construct was the null hypothesis (H0), according to which there is no statistically significant relationship between the integration factors and integration construct.

Results in Table 8 above shows that there is a weak concordance relationship (Wa = 0) between the respondents' agreement. The Chi-Square value (X2) for a 3 degree of freedom (df) was 11.094. Since the asymptotic significant value (p-value), which is less than (0.05), was 0.013, the study was unable to prove the null hypothesis (H0), according to which integration metrics and integration construct have no statistically significant relationship. This implies that there is a statistically significant relationship between the integration construct and the integration indicators.

- *Learning Analytics adoption readiness at Kibabii University*

In connection with establishing the level of readiness in adopting learning analytics at Kibabii university, the study interviewed twelve (12) teaching staff who are experts in online teaching selected purposively. The findings were presented in terms of thematic areas as discussed below.

Most teaching staff reckoned that the university in in the process on automation and the management is at the forefront towards supporting any technology will make activities within the university easier and efficient. They asserted that Learning analytics is a tool that when integrated with the LMS will allow lecturer access more information about the courses they are teaching. The university has budget allocations towards adoption of various ICTs and related technologies through set policies and frameworks. Using learning analytics requires ICT knowledge to be able to interpret the information well regarding online course and learning and teaching progress. Most of the systems used within the university are compatible can be easy be integrated with other third-party software to share data. The university has a role or function responsible for ensuring proper training and professional development of new technologies. The respondents were confident that the university has policies in data management and protection and will be able to oversee development of learning analytics policy. University have sufficient technical infrastructure to support data sharing & integration across systems

IV. CONCLUSION

The aim of this study was to evaluate readiness for adoption of learning analytics in Universities in Kenya. The study collected data on readiness for adoption of learning analytics where different indicators were given to respondents to rate them basing in their level of agreement on a Likert scale from Strongly Disagree (1), Disagree (2), Neither Agree nor Disagree (3), Agree (4) and to Strongly Agree (5).

Findings from the data collected show that most of the respondents agreed that there is readiness on adoption of Learning Analytics. This is because the mean of the response rates ranged between 3.65 and 4.08. On the Satisfaction construct, the response means of the respondents ranged from 3.65 to 4.08. Moreover, the findings on the Management Support construct indicated that most of the respondents agreed that there is readiness on the management towards support on the adoption of the learning analytics at the university with mean value of the responses ranging from 3.73 to 3.92. in addition, the findings indicated that respondents agreed that the university financial status on cost expenses is capable of adopting learning analytics. This was supported by mean value of the responses ranging from 3.73 to 3.89. Lastly, the findings reveal that most respondents agreed that there is adequate system integration to give room for the adoption of learning analytics tool with the existing systems. This was supported with a mean value ranging from 3.78 to 3.92 of the responses.

RECOMMENDATIONS

Usability of Learning Analytics makes its appropriate for its adoption. There is need for universities management to support its adoption by creating policies and procedures for its adoption. University should set aside finances for the facilitation of the technology and create information systems that can be easy be integrated with LA tool.

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