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ASSESSMENT OF LEARNING ANALYTICS FOR PRE PROFESSIONAL PROGRAMS AT KSAU-HS, ALAHSA, SAUDI ARABIA

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Abstract—: Learning analytics can improve teaching and learning practice by transforming the ways we support education processes. This study is based on the analysis of 256 students studying under Pre-Professional Programs of King Saud bin Abdulaziz University for Health Sciences in Saudi Arabia during the period Fall Semester 2018-19. The main research question s is: What is the application of learning analytics in Pre Professional Programs in Health Sciences University? The focus is on research approaches, methods and the evidence for learning analytics. The evidence was examined in relation to three validated propositions: i) the relationship between students Learning objectives and their academic achievements. ii) The relationship between students' performance and learning activity. iii). identifies students at risk in order to provide positive intervention. Analysis of LMS variables extracted from these analytic features established a statistically significant weakly positive correlation between hit activity, login activity and student examination results. These findings suggest that activity within LMS measured by logins; hit activity and results provide indicators of student academic performance. Lecturers involved in the study felt the analytic features provided them with a sense of student engagement with course modules and better understanding of their student cohorts.
Keywords: Learning Analytics (LA), Learning Management Systems (LMS), University Pre-Professional Program (UPPP);

I. INTRODUCTION

Definition:

Learning analytics is stated as "the measurement, collection, analysing and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [1]. Academic analytics refers to an application of the principles and tools of business intelligence to academia with the goal of improving educational institutions' decision-making and performance [2].

Background

All educational institutions generate and store large volumes of information about learners, learning and teaching process, but very few have explored the data they collect or used what they have learned [3, 4]. Researchers have studied student's success in online learning for a number of years. In previous years, researchers were primarily done using survey and interview data to predict student's success [5]. Recently, researchers have begun using learning analytics and academic analytics which is the "interpretation of a wide range of data produced by and gathered on behalf of students in order to measure academic progress, predict future performance, and spot potential issues" [6]. Despite the challenges of online delivery, the adoption of educational technologies has afforded a new opportunity to gain insight into student learning. As with most IT systems, the student's interactions with their online learning activities are captured and stored. These digital traces of log data can is 'mined' and analysed to identify patterns of learning behaviour that can provide guidance into education practice. This process has been described as learning analytics [7].

II. LITERATURE REVIEW

The introduction of learning analytic techniques into educational research now enables the analysis of student learning and their engagement in online learning activities like Learning Management Systems (LMS). Furthermore, Learning Analytics in the context of Higher Education is an appropriate tool for reflecting the learning behaviour of students and to provide suitable assistance from teachers or tutors. This individual or group support offers new ways of teaching and provides a way to reflect the learning behaviour of the student's. Another motivation behind the use of Learning Analytics in universities is to improve the inter-institutional cooperation, and the development of an agenda for the large community of students and teachers [8]. Higher education must strive to ensure that access means students can complete their education. Online learning is part of the solution to this problem. Student attrition in colleges and universities are at unacceptable rates and needs to be addressed as well. Data-driven decision making is already being used to help colleges identify and evaluate strategies that can improve retention. As data- driven decision making enters the Big Data and Learning Analytics era, these new approaches, may be part of the solution. Higher education administrators will do well by evaluating whether they can be used in their institutions and determining the role they can play [9]. On an international level, the recruitment, management and retention of students have become high level priorities for decision makers in institutions of Higher Education. Especially improving the student retention stats and the understanding of the reason behind or prediction of the attrition has come in the focus of attention due to the financial losses, lower graduation rates, and inferior school reputation in the eyes of all stakeholders [10]. Despite that Learning Analytics focuses strongly on the learning process, the results are still in the benefit for all stakeholders. Higher Education Institutions (HEIs) have entered in the era of 'Big Data' where they are collecting large volumes of data relating to their learners and the educational process. This vast amount of data is stored in the Student Information Systems (SIS) Academic Management Systems (AMS) etc.; including learner interactions with various educational technologies such as Learning/Course Management Systems (LMS/CMS), Moodle etc. and in various databases such as admissions files, library records and other systems [11].

The Society for Learning Analytics Research (SoLAR) defines the goals of LA as "understanding and optimizing learning process and the environments in which learning occurs". To date, most LA research has focused on individual learner performance and Learning Management System (LMS) data. The researcher collected data from the Learning Management System (LMS) which is used to study the relationship between student LMS use (e.g., posting discussion messages, completing quizzes) and academic achievement to predict the failing students which stated that "pedagogically meaningful information can be extracted from LMS- generated student tracking" [12]. Most active Blackboard Course reports have shown that students earning a final grade of D or F used the LMS with an average of 39% less than the students earning a grade of C or higher [13].The course structure on LMS, as determined by the instructor, has an effect on students' choices with regard to engagement and perceived values. Courses with more built-in discussion topics also tend to have more interaction in them [14]. The advantage of Learning Analytics using big-data mining is to predict students' future performance. Yet educators should pay more attention to improving the process of learners' achievement rather than predicting achievement [15].

In Saudi Arabia, at King Saud Bin Abdulaziz University for Health Science (KSAU-HS) a research was conducted on Utilization of Blackboard system among students and faculties. The study finding showed that the students with higher academic level utilize the blackboard function more than students in the lower academic level. Also there was a negative correlation between the number of theoretical and clinical course and the use of Blackboard functions by instructors [16]. At King Saud University (KSU), a study on usability and accessibility on LMS indicated that the e-learning software makes it easy to access and use to deliver course content materials, track the performance, and grade them.

The faculty members and staff agreed that the most helpful areas of the e-learning software include ease of access of teaching and learning materials, easy file management approaches, real time access to learning materials, and immediate feedback on the on-line quizzes. On the other hand, the study to evaluate the responses on the barriers to the adoption and use of the software for course materials showed that most of those teachers, and faculty staff members were those who had little or no prior experience with the software. The result supports the hypothesis that the software is easy to access and use [17].

In middle east, at Arabian Gulf University a research was conducted that stated a future strategy should focus on online course development and training faculty in developing more effective approaches for the courses. A good balance between content development, teaching strategies, and instructor possessed blended learning competencies will lead to high quality of teaching and learning outcomes on LMS [18]. At Qassim University a research was conducted for a blended medical education course that states LA techniques can help early predict underachieving students, and can be used as an early warning sign for timely intervention. The most important forecasters were factors which are reflecting engagement of the students and the consistency of using the online resources [19].

The Empirical Research on LA in the field of medical education is still in infancy, with more questions than answers. The research states that all the early studies collected data about learners from LMSs or online learning resources are encouraging and showed that patterns of online learning could be easily revealed as well as for predicting students' performance in various courses [20].

- The current study is important and unique in a way that no one performed any study for Evaluating Learning & Academic Analytics among students of pre professional program in the region of Al-Ahsa, KSA, as per our literature review.
- In this exploratory research, we seek to analyze educational data from our institution to advance our understanding of how learning unfolds in UPPP courses and how to improve course design by using this kind of information so that students learning engagement on LMS could be improved.
- The HOD gets to see the instructors' and students' activities on LMS for every course and can plan the next step. The course reports can be extracted from the system to evaluate the different online activities and to solve problems. This kind of framework improves interactivity between those who involved in the teaching and learning process, as it allows the course content to be reviewed and updated on regular basis.

III. RESEARCH QUESTION

This research aims at the elicitation of an overview on the advancement of the Learning & Academic Analytics field in Higher Education. The researchers used the Clow Model [21], where they will sample a group of data collected from Learning Management Systems, of University Pre-Professional Programs in King Saud Bin Abdulaziz University for Health Sciences. We used aggregate course-level data, rather than individual learner data with the goal of making such approaches generalizable across higher education institutions, while avoiding use of sensitive personal information.

Significance:

This paper is a study of the utilization and analyses of huge information in higher education. These huge amounts of information will improve and profit education system. Academic Institutions of higher education are operating in an increasingly complex and competitive environment. This paper identifies how wisely the data can be used to overcome many challenges faced by institutions of higher education for UPPP and to explore the potential use of Analytics in addressing these challenges.

IV. AIM / OBJECTIVES

This study aims to find out the relationship between the learning objectives and students performance in online activities of 3rd. level students of King Saud Bin Abdul-Aziz University for Health Science under University Pre Profession Program during AY 2018-2019.

Specific Objectives:

1. To determine the relationship between students Learning objectives and their academic achievements
2. To determine the relationship between students' performance and learning Activity.
3. To identify students at risk in order to provide positive intervention**.**

Secondary Objectives:

1. To determine all user activity in course content area on LMS.
2. To provide overall summary of course report on LMS.

V. METHODS

This is a descriptive cross sectional study conducted at King Saud Bin Abdul-Aziz University Health Sciences. We considered sampling a group of pre-professional students, who are enrolled to basic science courses. The number of students enrolled in 3rd.year N=902, number of courses = 5.

Study Area/Setting:
This study is conducted on the 3rd Level students (Female Branch) of King Saud Bin Abdul-Aziz University for Health Science during academic year of 2018-2019, Fall Semester.

Study Subjects:
In this study we included all the students of 3rd. Level under University Pre Professional Program irrespective of their specialty for single semester.

Inclusion Criteria:
1. All the students enrolled in Level 3 (Female Branch) under University Pre Professional Program.
2. All the students of 3rd. Level irrespective of their specialty are included.

Exclusion criteria:
1. Any student enrolled other than Level 3.

VI. STUDY DESIGN

This is a descriptive Cross Sectional study which is conducted on enrolled students of Level 3 during their Fall Semester in the University Pre Professional Program at King Saud Bin Abdul- Aziz University for Health Sciences, Al Ahsa.

VII. SAMPLE SIZE

Sample size is calculated through online software called Rao soft [22], where margin of error is 5%, 95% confidence interval is 256. The sample size (N) was 256. We added 10% to the sample size as non-response and to avoid any missing among participants during data collection, so the sample size was increased to 270.

Course Name	No. of students	30% of student	Sample size
Course-1	67	20.90	20
Course-2	126	38.10	38
Course-3	194	58.20	58
Course-4	189	56.70	57
Course-5	199	59.70	59
Course-6	127	38.10	38
		Total	**270**

VIII. SAMPLING TECHNIQUE

For the sampling technique, students enrolled for each course are randomly selected so that equal chance could be given to all students enrolled in particular course. The procedure is repeated until the required sample size is achieved. So that it removes bias from the selection procedure and should result in representative samples.

IX. DATA COLLECTION METHODS, INSTRUMENTS USED, MEASUREMENTS

The data was collected from Learning Management System (LMS) and Student's Information System (SIS). Data was extracted in the PDF format, saved as Microsoft Excel file. The Microsoft Excel file was further exported to the SPSS version 20 for the purpose of analysis. Obtained data was processed with IBM Statistical Package for Social Sciences (SPSS) version 20 for Windows. Descriptive statistics was calculated including frequencies and proportions for numerical variables and means with standard deviations (SD) for continuous variables. Inferential Statistics was calculated using Chi square test (for two categories) and ANOVA (analysis of variance) was used for variables with (more than 2 categories) to find out relationship between the learning objectives and students performance in online activities.

X. DATA MANAGEMENT AND ANALYSIS PLAN

The data was checked for completeness, perform coding and then enter into a computer by IBM Statistical Package for Social Sciences (SPSS v 20). Obtained data was analysed by using descriptive statistical tools (frequencies, percentages). Finally the data was presented in tables and graphs by using MS Office applications (MS Excel 2010 and MS Word 2010).

- Descriptive Statistics: was calculated with including frequencies and proportions for numerical variables and means with standard deviations (SD) for continuous variables.

- Inferential Statistics: was calculated using Chi square test (for two categories) and ANOVA (analysis of variance) was used for variables with (more than 2 categories) to find out relationship between the learning objectives and students performance in online activities. The relationship between depended variable and independent variables was measured using multiple regressions.
- For all the statistics analyses, α level was fixed at 0.05. And 0.2 β level with a corresponding power of 80% as suggested by Portney and Watkins [23, 24] to protect against type II error.

XI. RESULTS

The quantitative phase involved the measurement and analysis of data cleaned from Blackboard reporting to identify key statistical information regarding the student activity. Reports were extracted, anonymized and analyzed through Microsoft Excel and SPSS for existence of interdependencies, trends, patterns and relationships. Interrogation of LMS variables was conducted on login times, frequency of logins, student hits (click activity), grades, time spent on different courses.

Table No: 1 displays charts produced by the "overall activity report" within Blackboard for all courses. The course activity overview report enables lecturers to view the length of time students spend in modules and where they spend it. The overall summary of user activity could facilitate a lecturer in re-designing their course layout in order to place greater emphasis on such features. As shown in Table No 1 the blackboard activity is higher in Course 4, next to that Course 3 has the user activity, while the least activity is in Course 5. The focus shifts from the students to the lecturer as it enables lecturers to consider and evaluate their own teaching approach in light of what LMS features their students are using. These findings also suggest that lecturers learning about their students' use of LMS features through the analytic tools may encourage lecturers to make greater use of these data analytic tools with Blackboard Learn.

Table No: 1 shows the overall summary activity of blackboard user for all courses.

	Course 1	Course 2	Course 3	Course 4	Course 5	Course 6
Announcements	26 (0.22%)	101 (0.61%)	87 (0.038%)	426 (1.5%)	164 (3.38%)	153 (0.01%)
Content	11581 (99.26%)	16413 (98.84%)	20004 (88.15%)	19843 (70.02%)	4578 (94.48%)	20895 (96.67%
Course email	6 (0.05%)	10 (0.06%)	1046 (4.61%)	265 (0.94%)	19 (0.039%)	37 (0.17%)
Course tools area	6 (0.05%)	23 (0.14%)	358 (1.58%)	210 (0.74%)	26 (0.54%)	39 (0.18%)
Discussion board	41 (0.35%)	32 (0.19%)	139 (0.61%)	1393 (5%)	30 (0.62%)	56 (0.26%)
Groups	6 (0.05%)	22 (0.13%)	631 (2.78%)	3283 (11.58%)	14 (0.29%)	35 (0.16%)
Instructor grade book	0	0	234 (1.03%)	2766 (9.76%)	7 (0.14%)	397 (1.87%)
Student gradebook	0	0	176 (0.78%)	20 (0.07%)	3 (0.06%)	1(0.00)
Tasks	0	1	12 (0.05%)	44 (0.16%)	1 (0.02%)	1(0.00%)
Total	**11666**	**16602**	**22687**	**28250**	**4842**	**21614**

Chart No: 1 shows the overall weekly activity of blackboard in whole fall semester for different courses. The overall weekly activity in blackboard for Course 6 is more than any other courses. These results identified a strong relationship between log in frequency and course outcome. This identify active site engagement and time on task as an effective predictor of course outcomes in LMSs

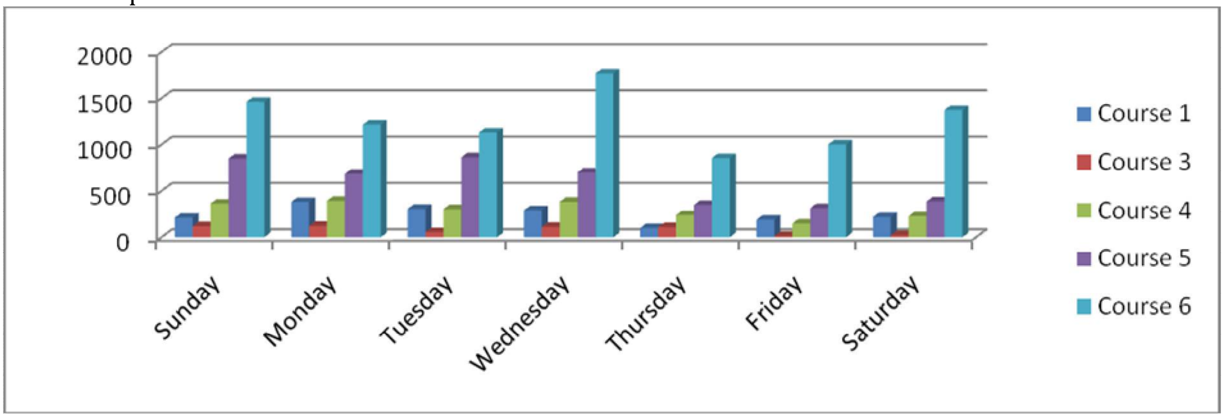

Chart No: 1 shows the overall weekly activity of blackboard

Chart No: 2 show the weekly activity of blackboard in different courses. This report illustrates user activity of different courses in each days of the week of the student groups involved in the study. From this figure it's clearly understood that for all courses the usage of blackboard is more in the working days when compared to week days. The weekly activity of Course 4 is higher in Tuesday, but on Thursday for Course 3 and Course 4 the activities are equal, while the least activity in blackboard was to Course 1.

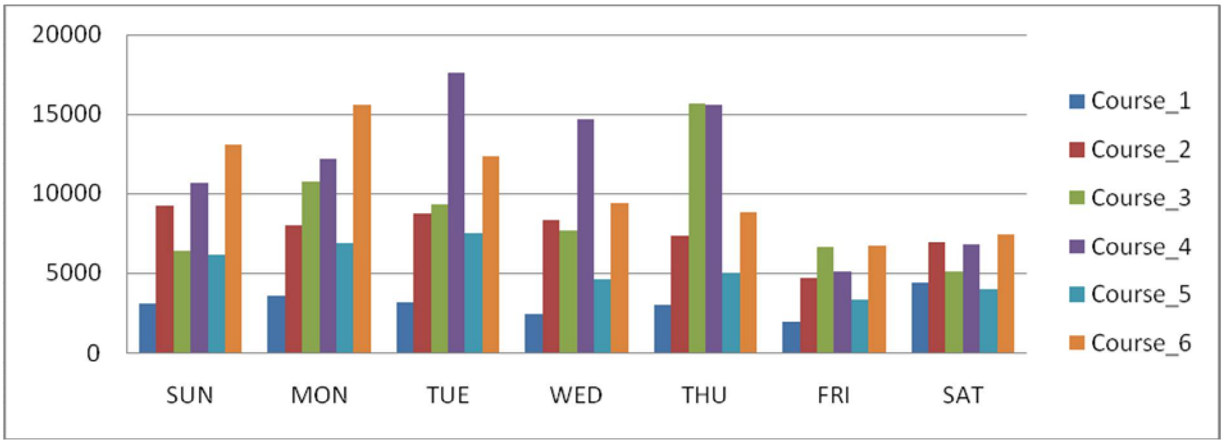

Chart No: 2 shows the weekly activity of blackboard in different courses

This report illustrates user activity in all areas of the module by 24hours of the day for the student groups involved in the different study courses. The users are active during the working hours ie it starts from 8 am onwards until 11pm. For the entire Course the activity in blackboard is peak at 8 pm and 11 pm.

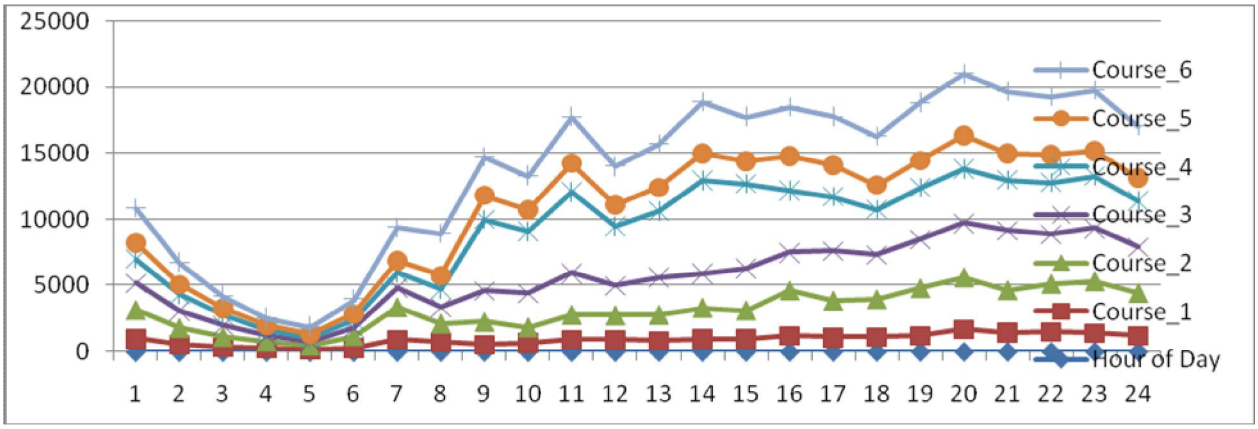

Chart No: 3 shows the 24 hours activity of blackboard in different courses

Chart No: 4 displays the average time per active student groups involved in the different Courses. The average time activity of blackboard to Course 6 and Course 5 is 69.97% and 65.56%, while for Course 5 its 21.29%.

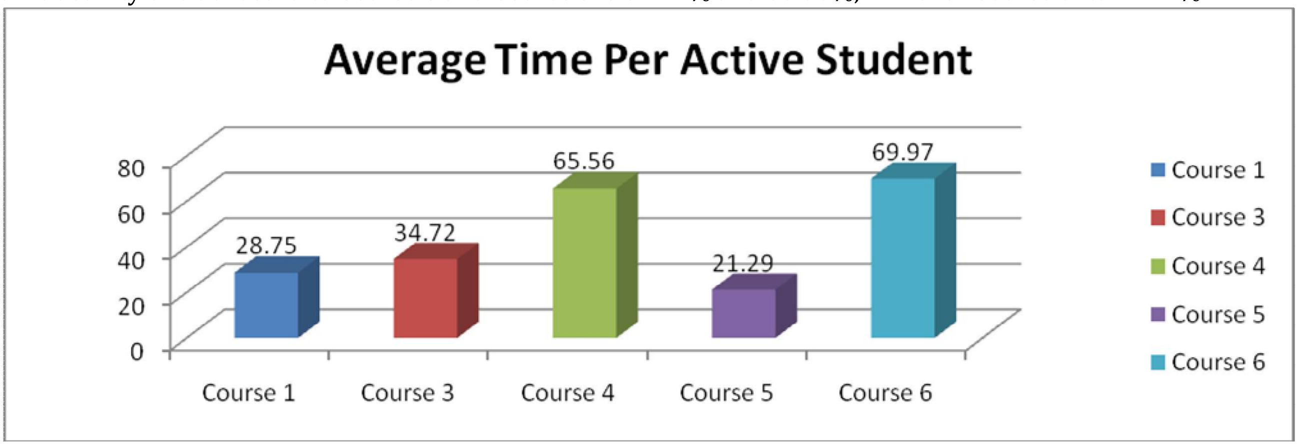

Chart No: 4 showing the average time per active student in different subjects

Chart No: 5 shows that the overall activity of blackboard in terms of assignments and learning materials in different courses in one semester. The assignments and the learning materials uploaded in the blackboard for Course 3 is comparative higher than any other courses. These findings may be influenced by high performance in exams at the end of level 3 programs whereby students are aiming to achieve good grades and not just pass the course. It does however provide an indicator of student activity within LMS and these findings suggest the amount of hit activity within Blackboard Learn may positively influence students 'examination results.

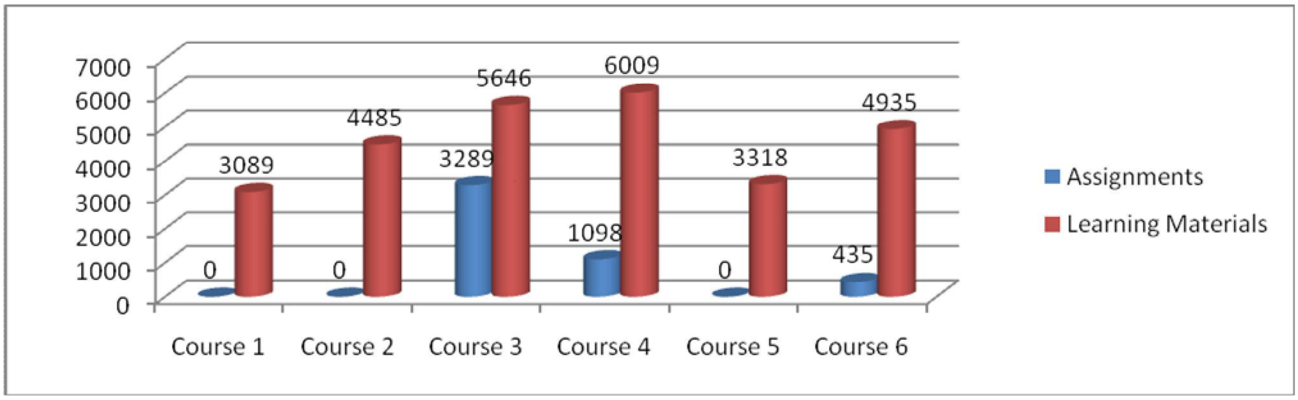

Chart No: 5 shows the overall activity in different course

Table 2 Shows the correlation analysis for the students' performance in different course with the their overall activity in blackboard

	R	R2	p- value	Significance
Course 1	.152	0.023	0.247	
Course 2	.323	0.104	0.00*	<0.05
Course 3	.226	0.051	0.02*	<0.05
Course 4	.256	0.065	0.00*	<0.05
Course 5	.050	0.0025	0.485	
Course 6	.100	0.01	0.260	

Table 2 shows the correlation analysis for the students' performance in different course with the overall activity in blackboard. These findings suggest that frequency of login and hit activity in Blackboard may serve as effective predictors of course performance. Relationships between LMS variables and their overall grades strengthened positively based on academic progression. Course 2, Course 3 & Course 4 demonstrated a significant relationship between the students' performance and their overall activity in the blackboard (p-value is < 0.05). No other statistically significant correlation was established for the remaining courses (Course 1, Course 5, and Course 6)

The **R** value represents the simple correlation and is 0.323 for Course 2, 0.226 for Course 3 and 0.256 for Course 4 which indicates a weak positive degree of correlation. The **R^2** value indicates how much of the total variation in the dependent variable students' performance in these courses can be explained by the independent variable, activity in blackboard. In this case 10.4 % of variation in students' performance is explained by the relationship of user activity in blackboard for Course 2, 5.1% of variation in students' performance is explained by the relationship of user activity in blackboard for Course 3, 6.5% of variation in students' performance is explained by the relationship of user activity in blackboard for Course 4 p-value is < 0.05. So, there is a significant relationship between the students' performance and their overall activity in the blackboard.

Table No: 3 shows the students at risk for different courses.

Courses	Hits at retention center (%)
Course-1	1(.01%)
Course-4	8(0.03%)
Course-5	1(0.01%)

Blackboard Learn has an inbuilt early warning system called the Retention Center. Using the Retention Center feature within Blackboard Learn, lecturers are able to identify the number of times the lecturer for the course try to open the retention center. Table no: 3 represents the frequency of students at risk in different courses, where in Course 4 the retention is 8 (0.03) but for Course 1 and Course 5 only one time the lectures of the corresponding course open the retention center.

XII. DISCUSSION

In this study, we investigated the variables that best correlate with students' Learning objectives and their academic achievements, the relationship between students' performance and learning activity and students at risks. We have expanded over the previous studies [3, 7] and included data about access, hits, time, forums, communications, and as well as formative & summative assessments for AY 2018-19 during Fall Semester. Our results indicated that the engagement indicators showed consistent and significantly higher correlations with the students' performance across all categories of measurement.

In contrast to the simple generic metrics, which showed inconsistent and relatively weaker correlations with students' performance? Parameters such as time and hits (the most generic metrics) were the weakest [19], and parameters that reflected motivation and disposition such as taking the optional formative assessments, frequency of access, content creation and grade book were the best indicators of students' performance. In this study, we opted for using only tracking variables collected from students' use of the LMS and the calculated engagement parameters. Engagement has been shown to be an important factor for the adoption of learning technology. Aspects of engagement, like involvement in the learning process, time spent on a task and compliance has been shown to positively correlate with effective learning and positive outcome. Since engagement has different dimensions or aspects; therefore, there are different ways to measure engagements [25, 26].

In this study, we have explored the potential of LA to measure information produced by Blackboard Learn analytic features to assess the impact of student engagement with same. Extraction of LMS variables i.e. logins, content hits, overall module hits and MCQ assessments demonstrated statistically weakly positive correlation with exam performance, suggesting that these variables can serve as effective predictors of student academic performance. The study shows that the data and reporting features facilitate academic staff in learning more about the activity of their students in Blackboard. LA is automatic, effortless, samples a large number of indicators, and offers a quantifiable risk index [1, 3]. Finally the parameters of engagement showed significant positive correlations with students' performance [19], especially the parameters that reflected motivation and self-regulation such as trying formative assessments, assignments, frequency of logging, and creation of new content. Furthermore the higher education institutions give sufficient workshops and resources to faculty for using the Learning Management Systems to enhance their teaching and learning skills. Understanding the usage patterns of instructional technology tools such as the LMS by faculty members and students, institutional support personnel and administration can make better, data-informed decisions regarding future technology procurement and support prioritization to help ensure that instructional needs are being met [27].

XIII. CONCLUSION

This research presented a study on the use of LA in UPPP, Al Ahsa and examined it using the data from Learning Management Systems – Blackboard Learn. The research was set out to identify quantitative markers that correlate with to study the relationship between students Learning objectives and their academic achievements, the relationship between students' performance and learning activity and students at risk. We also calculated engagement indicators that would reflect self-motivation and consistency of interest in using the LMS resources. The study was carried for Fall Semester 2018-19 with female students of Level-3. The courses involved for study where Basic Sciences. We would look forward for extension of our research for different semesters, with multiple disciplines, for all levels, with both genders of students and extensively if multiple campuses are available within a university. This study is not without limitations, being quantitative in nature like most LA studies which is our most important limitation, although we have tried to link our findings to theories of engagement, there is still a long road ahead to replicate these findings and build generalizable approaches.

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REFERENCES

1. Siemens, G., &Gašević, D. (2012). Special Issue on Learning and Knowledge Analytics. Educational Technology & Society, 15(3), 1–163.
2. Campbell, J. P., De Blois, P. B., &Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. Educause Review, 42(4), 40-57. Retrieved from http://www.educause.edu/ero/article/academicanalytics-new-tool-new-era
3. Macfadyen, L. P., & Dawson, S. Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan. Educational Technology &Society, 15(3) (2012), 149–163.
4. Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. Big data: The next frontier for innovation, competition and productivity. McKinsey Global Institute (2011).

5. Chyung, S. Y. (2001). Systematic and systemic approaches to reducing attrition rates in online higher education. American Journal of Distance Education, 15(3), 36–49.
6. Johnson, L., Smith, R., Willis, H., Levine, A., & Haywood, K., (2011). The 2011Horizon Report. Austin, Texas: The New Media Consortium. Retrieved from http://www.nmc.org/pdf/2011-Horizon-Report.pdf
7. Gašević, Dragan, Shane Dawson, and George Siemens. "Let's not forget: Learning analytics are about learning." TechTrends 59.1 (2015): 64-71.
8. Atif, A., Richards, D., Bilgin, A., &Marrone, M. (2013). Learning analytics in higher education: a summary of tools and approaches. In ASCILITE-Australian Society for Computers in Learning in Tertiary Education Annual Conference (pp. 68-72). Australasian Society for Computers in Learning in Tertiary Education.
9. Picciano, Anthony G. "The evolution of big data and learning analytics in American higher education." Journal of Asynchronous Learning Networks 16.3 (2012): 9-20.
10. Delen, D. (2010). A comparative analysis of machine learning techniques for student retention management. Decision Support Systems, 49(4), 498-506.
11. Tair, M. A. & El-Halees, A. (2012). Mining Educational Data to Improve Students' Performance: A Case Study. International Journal of Information and Communication Technology Research, 2(2), 140-146.
12. Macfadyen, L.P. & Dawson, S. (2010) Mining LMS data to develop an 'early warning system' for educators: A proof of concept, Computers & Education, 54, 2, (2010), 588-599.
13. Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. The Internet and Higher Education, 14(2), 89-97. Roll, I., Macfadyen, L. P., & Sandilands, D. (2015, March). Evaluating the
14. Relationship Between Course Structure, Learner Activity, and Perceived Value of Online Courses. In Proceedings of the Second (2015) ACM Conference on Learning@ Scale (pp. 385-388). ACM.
15. Yu, Taeho, and Il-Hyun Jo. "Educational technology approach toward learning analytics: Relationship between student online behavior and learning performance in higher education." Proceedings of the Fourth International Conference on Learning Analytics and Knowledge. ACM, 2014.
16. Habib, Farida, et al. "Evaluation of the Utilization of e-blackboard system among students and faculties in King Saud Ben Abdulaziz University for Health Science." Journal of American Science 8.7 (2012).
17. Alturki, Uthman T., and Ahmed Aldraiweesh. "Evaluating the Usability And Accessibility Of LMS" Blackboard" At King Saud University." Contemporary Issues in Education Research (Online) 9.1 (2016): 33.
18. Ismail, Alajab Mohammed Alajab, and Ahamed Ali Salih. "The Impact of Blackboard LMS on Teaching Research Method Course for Technology Studies Graduate Students at the Arabian Gulf University."International Journal of Information and Education Technology, Vol. 8, No. 2, February
19. Saqr, M., Fors, U., &Tedre, M. (2017). How learning analytics can early predict under- achieving students in a blended medical education course. Medical teacher, 39(7), 757-767.
20. Saqr, Mohammed. "A literature review of empirical research on learning analytics in medical education." International Journal of Health Sciences 12.2 (2018): 78-82.
21. Clow, D. (2013). An overview of learning analytics. Teaching in Higher Education, 18(6), 683-695.
22. Web survey software, online surveys, email surveys from Raosoft, Inc.Raosoft.com http://www.raosoft.com
23. Faul, F., Erdfelder, E, Buchner, A., & Lang, A-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41(4), 1149-1160.
24. Portney, L., & Watkins, M. (2009). Foundations of clinical Research (3rd ed.). Upper Saddle River, NJ: Prentice-Hall.
25. Ballard J, Butler PI. 2016. Learner enhanced technology. J Appl Research for HE. 8:18–43.
26. Cruz-Benito J, Ther_on R, Garc_ıa-Pe~nalvo FJ, Pizarro Lucas E. 2015. Discovering usage behaviors and engagement in an educational Virtual World. Computer Human Behavior. 47:18–25.
27. Rhode, Jason, et al. "Understanding Faculty Use of the Learning Management System." Online Learning 21.3 (2017): 68-86.

