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Learning analytics in the EFL classroom: Technology as a forecasting tool

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Abstract

Ideal e-learning management systems (eLMSs) offer many applications given their huge dataset. They are a repository of information needed for the smooth functioning of the teaching-learning process in tech-enabled spaces. Databases created in these analytical systems permit not only the retrieval of data but also the updation of changing learning and pedagogical needs. This study aims to provide insights into predictive educational benefits to EFL classrooms as a result of the application of analytic methods by using grades in final exam scores of 25 EFL female learners of an undergraduate course at Prince Sattam bin Abdulaziz University (PSAU), Saudi Arabia. The study also analyzed the learning behaviours on Blackboard. Results show that lesson videos have the highest hit out of the three parameters (lesson videos, textual notes, practice exercises) offered on the e-learning platform (BlackBoard), followed by practice questions, and the least visitations were registered for the textual notes. Correlation between the learning videos (related to the three literature lessons taught) and final grades showed statistical significance at 95% confidence level, in addition to the factor of topic completion by the learners being a highly influencing factor in final grades. As a predictive model, Learning Analytics (LA) established that videos are a preferred way of learning English in the Saudi EFL context. The results of the study are likely to be of significance to course developers, teachers, and learners of EFL.

Keywords: English as a foreign language, learning management systems, learning analytics, predictive model

Public Interest Statement

Ideal e-learning management systems (eLMSs) offer many applications given their huge dataset. They are a repository of information needed for the smooth functioning of the teaching-learning process in tech-enabled spaces. Databases created in these analytical systems permit not only the retrieval of data but also the updation of changing learning and pedagogical needs. This article, however, would be of great use to all those interested in CALL, CALT, including EFL teachers and learners and policy makers.

Introduction

The situations made imminent by the geopolitical developments of the past few years have paved the way for tremendous growth in the education sector with technology especially seeing integration into the teaching and training pedagogy (Aghagolzadeh & Davari, 2017). The Learning Management Systems and their integrated feature of LA have helped teachers and learners significantly in tackling the challenges of English language learning in EFL scenarios (Al-khresheh, 2022). Their biggest strength lies in the personalised and timely feedback that is now possible for teachers to give, ensuring early course correction for the learners.

Teachers and instructors in classroom teaching have few, if any, means to keep individualized track of learner engagement and motivation as there is only so much that human intervention can achieve, especially when the learners are many to a classroom and a varied lot. Further, identification and forecasting of problems is another challenge which, if tackled, can help teachers be better equipped and move positively towards achievement of learning objectives. LMS and LA use large data towards ensuring optimum participation of learners, their meaningful engagement in the learning process, and comprehension (Baker et al., 2016). In the same way they can be applied to identify potential problems early on in a course and predict future cohorts. In short, their contributions in the long run can cover the fields of pedagogy, active and empowered learning, learner issues such as dropout and course completion challenges (Reinders, 2018).

Though applicable in all language domains, learning analytics can have some very useful implications in language learning to monitor academic and non-academic indicators such as achievement test performances, attendance, attainment of specific learning goals such as vocabulary acquisition, and the relationship between learning and time taken (Zeide & Nissenbaum, 2018). In addition, challenges faced by individual learners can also be identified such as issues in acquiring certain grammatical features, syntax etc. Once identified, individual or group guidance can be made available to the learners, taking the shape of a very useful pedagogical tool that teachers can apply with ease. At the policy making level, LA and management systems can answer questions pertaining formulation of language education policy, teachers' needs, alignment of language education to national learning goals, nature of learner proficiency, and learners' needs (Aghagolzadeh & Davari, 2017). What makes these tools especially effective is the fact contrary to general beliefs, large scale data are not necessarily needed to derive their benefits: The information teachers already have about their learners can be just as useful for learning analysis.

History of education has shown that to enhance the quality of the education system and to improve the enrolments and involvement of scholars via distance and combined learning different LMS are adopted by different continents specifically in Africa and Tanzania. For implementing eLMS educational institutions have been devoting thousands of dollars. You may observe changes in your text by looking at the orange coloring. But in recent years, there has been a lot of interest in researching how these systems affect students' performance.

The impact of LMS usage on students' learning performance has been determined by studies using data from users' opinions and subjective interpretation through questionnaires. Typically, there is a chance of distortion or low reliability when using such data. This led to studies such as Mwalumbwe and Mtebe (2017) which built and created a learning analytics tool and utilized it to ascertain the relationship between the use of an LMS and student performance. Using a newly built learning analytics tool, data from the LMS log of two courses offered at Mbeya University of Science and Technology (MUST) were extracted. Results from research showed that posts, peer interaction, and exercises were determined to be significant factors for students' academic achievement in blended learning. It was found that there was an insignificant role of time spent in LMS, number of downloads and login frequency on the learning routine of scholars. They also examined the consequences of these observations in improving scholars' students learning.

Such studies played a great role during the Covid-19 pandemic when there was a high demand for using e-learning environments. Due to precautionary measures and social distancing, it was important to find out the best means to ensure the continuity of study by institutions and the best mode was e-learning. This is the main reason that this area of LA research has recently received significant attention. For the past few decades, has been making headlines and catching the eye of higher education globally.

Research questions

LA has been in the limelight as a predictive tool in learning patterns and hence, seen as being of immense use in improving learners' performance. Apart from the basic metric that it helps calculate and formulate answers to sophisticated concerns such as which methods are of little or no use in language learning in a class with mixed abilities learners such as is typically seen ion the Saudi EFL context. Accordingly, this study tries to answer the following questions:

1. In an e-learning EFL class, what learning patterns/ parameters could be successfully gauged using LA?
2. What is the predictive value of LA in the EFL context of Saudi Arabia in relation to performance in assessment tests?

Literature review

LA is a field of database creation using LMS that typically comprises the stages in data processing from collection to reporting with the expressed aim of enhancing learning (Clow, 2013; Viberg et al., 2018). Hence, Alyahyan et al. (2020) conducted a literature review on predicting academic success in higher education. They were focussed on best practices required for learning process and found that, in higher education, learning analytics plays an important role in understanding the pattern of grades and to improvise the students' behaviors and grades it is mandatory to monitor them closely. For this learning analytics was required especially during Covid-19 pandemic as it became necessary to look for learning tools and their impact on the learning process.

In LMS most of the learning is done by adopting an online or blended mode (Jo et al., 2014). For this fact, institutions should keep an eye to measure the quality and strength of the application of LMS in Institutions. There are few studies that prove correlation between LMS usage with the performance of scholars (Kotsiantis et al., 2013; Jo et al., 2014; Macfadyen & Dawson, 2010; Whitmer et al., 2012). Moreover, some researchers focused on students' satisfaction with courses offered via LMS (e.g., Naveh et al., 2012). LMS accumulates enormous amounts of data on scholars' behaviour or how it can be useful to give information and how it enhances their engagement in learning (Beer et al., 2010). By analyzing the application of LMS via log data it is possible to grade learning and even to predict the possible learning achievement of learners in EFL classrooms (Naveh et al., 2012). With these kinds of predictions, we can easily identify struggling learners in need of academic help (MAcfadye & Dawson, 2010). Further, to assess the quality of online postings Learning Analytics tools can be easily used to get data and perform predictions based on analysis (Nistor et al., 2015). It is easy to visualize and predict usage behaviors in the LA system (Scheffel et al., 2011). Some researchers acquired different LA tools to analyze the data offered by log data stored in LMS databases. In 2014, Yu and Jo (2014) worked on factors that impact the academic grades of learners via using a data log collected from Moodle with 84 students in South Korean University. They observed that while learning online there is a significant effect of total studying time, interaction with peers, regularity of learning interval, and the number of downloads on students' grades. Jo et al. (2014) worked in the same field and used log data set as a factor to find out scholars' performance in courses offered via Moodle. They identified "Candidates for proxy variables". These researchers worked on a commercial e-learning course and used the identified variables from 200 scholars. The study revealed the fact that an irregular learning interval proved to have a correlation between learning performance and academic achievement of learners in online mode.

For data collection from logs, Kotsiantis et al. (2013) used an LA tool called Moodle Parser. They juggled and identified successful learners in combined learning courses through students' activities in Moodle. They observed a direct correlation between learners' failure with their negative approach and perceptions towards Moodle: Good grades were directly proportional to the increased level of Moodle use by learners. They collected data from 337 students enrolled for a 3-year course with the usage of Moodle at the University of Patras, Greece. Similarly, a study at Central Queensland University using a sample of 92,799 students found that the more views or visits to the course by the learner, the higher the level of final grades achieved by learners while learning via online course. They reported a statistically significant correlation between the number of page views and students' final grades (Beer et al., 2010).

In recent study based on AI techniques to predict students learning difficultis using LMS at King Fahad University is El Koshery (2023). This study developed a prediction model to identify potential e-LMS usage challenges for students. In this research, ten well stated machine learning (ML) algorithms were used: Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), SGD Classifier, Multinomial NB, K-Neighbors Classifier, Ridge Classifier, Closest Centroid, Complement NB, and Bernoulli NB. Academic performance were predicted from educational data by Amrieh et al. (2016).They used ensemble methods for mining educational data and concluded that it is far better to use few methods for mining educational data to check students' performance.

Learning analytics (LA)

The conception of LMS goes much beyond the boundaries of the classrooms as they aim to create active teacher learning communities that foster professional development and enrichment as well as teacher collaboration (Al-khresheh, 2022). This is where the idea of big data analytics takes germ as comparison of data across classes can help identify learning patterns and help teachers identify early on the outliers. Classroom based LMS such as Moodle, SmartKlass, ClassDojo, and GoSkills help keep close and multifarious tabs on the learning activities such as lesson repeats, access to notes, practice exercises etc. which help generate viable and authentic learning behavior data. With access to both teachers and learners, this proves to be a useful resource in pedagogy and materials modification and autonomous learning (Aghagolzadeh & Davari, 2017). The system of badges and points allotment for task completion or revisit also ensures learner engagement. Close monitoring of these data gives teachers an invaluable upper hand in flagging learning issues early on, checking learners' communication abilities, identifying the reticent learners, ensuring optimal participation, and modifying assignments and tests to enable learners to do their best. The point to be noted is that learners themselves have as much access to these data as the instructors, making them active agents in the learning process. This working collaboratively towards common goals keeps the learners motivated while giving them a sense of control over their learning and also making them partners in the responsibility to learn. Overall, the unique features of LMS help the teachers know their learners better and understand their needs more actively.

LA approach is completely driven by data to understand learning behaviors and to improve the learning spaces. Some examples of these activities are monitoring learner engagement in the learning process; understand how feedback impacts learning and performance in general; deciding strategies derived from data analysis that may help poor performers do better; improving course materials to address learner needs. Agudo-Peregrina (2012) predicted academic performance with LA in virtual learning environments and based on the agents involved in the learning process, usage frequency, and participation method, respectively, three separate classes have been created. The main conclusions of the study are as follows: a) agent-based classifications provide a better explanation of student academic performance; b) at least one element in each typology predicts academic performance; and c) student-teacher, student-student, evaluating students, and active interactions, respectively, have a significant impact on academic performance, while the other types of interactions do not.

In 2017, Saqr and Fors invesitgated the impact of LA in the early prediction of underachieving students in the combined educational course in medical science. The purpose of this study was to find quantitative indicators gathered from the online actions of students that might be correlated with students' final performance and to look into the feasibility of determining the likelihood that a student will fail or drop out of a course. After completion of the course, they concluded that they were able to achieve the prediction of the accuracy level of final grades with 63.5% accuracy. They found that they were able to predict 53.9% of students who were at risk. They applied a binary logistic model which improved the prediction level to 80.8%. Their results showed that the highest level of importance was predictors factors which were reflecting the engagement of learners and their uniformity of using the online resources. Finally, they concluded that online activities by using LA techniques can improve prediction in the early detection of scholars who were underachievers. This can be further extended to a warning sign for timely interventions on the early stages.

Athani et al. (2017) investigated student performance predictors using multiclass support vector classification algorithm. They used ten ML algorithms for building a prediction system which was based on AIs. This algorithm was used for the prediction of issues faced by scholars while using e-learning management system. It also helped teachers to decide which technology was best for learners in a university. Bajpai et al. (2019) discussed the comparison between different machine learning algorithms and tried to extract the most appropriate and efficient algorithm which is suitable for prediction of researchers' academic performance. They found that some of the algorithms were trivial to implement and while some had issues in implementing it.

Many researchers worked in the field to identify the best algorithms which affect the effectiveness of sessions such as family commitment, study environment and teaching style. This also helps in predicting students' academic performance (Al-Ahdal, 2020; Dietz-Uhler & Hurn, 2013; Jayaprakash, 2020; Ghorbani & Ghousi, 2020; Mödritscher, 2013; Namoun & Alshanqiti, 2021; Scheffel, 2011).

Recently in 2021, Abdallah with his co-researcher did a systematic literature review to predict scholars' performance via data mining and LA techniques. In the past few decades, we have seen a significant amount of research done on the prediction of students' academic performance in the education system. Though the learning outcomes are based on teaching, prognosticating the attainment of students' outcomes is still unexplored. To understand the intelligent techniques which are used for the prediction of students' performance an ample amount of investigations were done between 2010 to 2020. These kinds of results are beneficial in the academic success of learners for better learning outcomes. They synthesized and analysed 62 relevant papers with a focus on perceptions:

1) Prediction of methods in which the learning outcomes.
2) Predictive analytics models developed for forecasting and predicting learning outcomes in learning analytics.
3) The major factors impacting student outcomes.

Methods

Research design

Since the shift to online education in the wake of the pandemic, universities across Saudi Arabia have stuck with technology blended learning since the outcomes were found to be more beneficial in this mode than the conventional classroom lecture method of the earlier times. The current study set out to apply LA to examine the language learning behaviors of 25 EFL female undergraduate learners at PSAU, KSA The study was carried out in the second semester of the academic year 1444 AH for a period of six weeks of blended learning using BlackBoard.

Paritcipants

The learner group chosen for this study were 25 second year undergraduate EFL learners. All participants were females, and the median age of the group was 19.8 years. Given the high intake of learners in the EFL courses for their employability quotient, the inclusion criteria were access to online materials for a minimum of two times for the online course content of EFL in the current semester, and a consistent CG of 2.5 and above in the last three semesters at PSAU. In the blended model, only an equal number of EFL classes are held in the physical and the online mode (using the BlackBoard tool), but all assignments are submitted via BB. To keep the data focussed, this study analysed only the online materials access (which included (i) teacher's readings and relevant video clippings; (ii) textual notes and; (iii) practice exercises), and performance in the assessment test conducted by the University. Moreover, teacher's role as expressed in the completion of topics in the blended learning classes was also assessed in correlation to the learning behavior patterns. This was considered an important factor in the study to evaluate the hypothesis that interactive learning programs can replace the teacher in EFL classes.

Data buildings

Databases created in these analytical systems permit not only the retrieval of data but also the updation of changing learning and pedagogical needs. Accordingly, over a period of six weeks the researcher extracted learning behavior data of 25 learners from the currently used BlackBoard learning portal. In all, three English literature lessons were taken up with 14 value areas or topics which were targeted to be imparted as part of the learning objectives. The entire set of learning materials were online. Standard features of BB were used to capture log-in behavior patterns for the three parameters, teacher's readings and videos (related to the three literature lessons), textual notes, and practice exercises.

Literature components in the Introduction to Literature book include questions based on basic to higher order thinking skills (HOTS) and BB marked a component complete only if the participant answered three HOTS questions correctly in a row. Thus, all correct answers for the entire learner group were taken as one body of data and transferred to MS Excel for statistical analysis. As far as the role of the LMS is concerned, it was limited to recording and storing learning behaviors while different perspectives of the aggregated data were obtained on Excel. The predictive model was created using standard regression analysis. The videos included film clippings on simialr themes as the literature items, and brief podcasts on their themes.

Data analysis

Table 1 below summarizes the grade scale applied at PSAU.

Table 1

PSAU Grade Scale

Grade	Scale	Scale 2	Grade Description
A+	4.76 - 5.00	95.00 - 100.00	Exceptional
A	4.51 - 4.75	90.00 - 94.99	Excellent
B+	4.01 - 4.50	85.00 - 89.99	Superior
B	3.51 - 4.00	80.00 - 84.99	Very Good
C+	3.01 - 3.50	75.00 - 79.99	Above Average
C	2.51 - 3.00	70.00 - 74.99	Good
D+	2.01 - 2.50	65.00 - 69.99	High Pass
D	1.01 - 2.00	60.00 - 64.99	Pass
F	0.00 - 1.00	0.00 - 59.99	Fail
DN	0.00 - 1.00	0.00 - 59.99	Denial
IC			Incomplete

Results

RQ1: In an e-learning EFL class, what learning patterns/ parameters could be successfully gauged using LA?

As can be seen, the measure of student success at PSAU is 60% (D) with grades the higher grades being categorized over a scale ranging from High Pass (D+ at 65.00 - 69.99) to Excellent (A+ at 95.00 - 100.00). In the results obtained from the university assessment test at the end of the semester, fifty percent of the participants passed the course. The highest percentage score was 96% and lowest was 11%. Table 2 below summarizes the data of online materials visitations by learners in each grade category, topics completed by the learners in that grade, and assessment test performance. Note: All data in Table 2 are expressed as average frequencies rounded off to the nearest zero. Table 2 indicates that lesson videos have the highest hit out of the three parameters (lesson videos, textual notes, practice exercises) offered on the e-learning platform (BlackBoard), followed by practice questions, and the least visitations were registered for the textual notes.

Table 2

Assessment test performance, Frequency of visitation on BB, Topics completed (avg.)

Assessment test Grade	Number of learners	Teacher's readings and video clippings	Textual notes	Practice exercises	Topics completed (avg.) out of a max of 14
A+	03	29	09	24	12
A	01	23	02	19	11
B+	01	23	03	19	09
B	03	18	01	16	07
C+	04	18	01	15	05
C	04	15	01	11	03
D+	01	09	01	05	04
D	01	05	01	03	04
F	01	05	00	02	03
DN	06	03	00	03	02
IC	00	-	-	-	-

RQ2: What is the predictive value of LA in the EFL context of Saudi Arabia in relation to performance in assessment tests?

The study applied multiple regression to arrive at a predictive learning behavior model based on the data above. There were four independent variables: i. Aggregated teacher's readings and videos; ii. textual notes; iii. practice exercises; iv. topics completed by the learner. The university assessment test grade was the dependent variable. Correlations between final grade scores and aggregated values of the three independent variables were computed and found as follows in Table 3.

Table 3

Correlations between variables

Variable	Coefficient of determination with final grade score	Whether statistically significant
Teacher's readings and videos	43%	yes
Textual notes	02%	no
Practice exercises	18%	yes
Topics completed	21%	yes

The correlation between Teacher's readings and videos and assessment grade was statistically significant at 95% confidence level, the highest amongst the four independent variables tested in this study. In other words, learning success was closely related to teacher's lecture and related videos in the BB portal. This predicts learners' high frequency use of these materials in an e-learning EFL scenario. Similarly, topic completion by the learners was positively correlated with assessment grades at 21% confidence level, predicting the importance of guiding and motivating learners towards using e-learning to the optimum. This is followed closely by practice exercises at 18%, predicting learners' performance dependence on these. The variable which least affected assessment grade was textual notes which showed negligible visitation by the participants.

Discussion

This study explored the learning paradigm that LA can develop. The finding reported that lesson videos have the highest hit out of the three parameters (lesson videos, textual notes, practice exercises) offered on the e-learning platform (BlackBoard), followed by practice questions, and the least visitations were registered for the textual notes. Reigeluth et al. (2016) showed that time-based learning has been replaced by proficiency-based learning, norm-based assessments by criteria-based tests, passive and teacher-directed students by active and self-supervised students. This finding shows that shift in education has given rise to novel circumstances like personalized instruction, behaviour analysis of students, and the use of alternative evaluation methods (Lee et al. 2018). Consequently, this study showed how LA helps in identifying the learning behaviors by analyzing learning patterns. One of the most important aims of learning analytics is to access meaningful outcomes from virtual learning environments and to expand learning outcomes in online environments.

Results also indicated a close correlation between three of the variables. These findings are of great significance in the Saudi EFL context as they establish the redundancy of textual notes uploaded on learning platforms for learner reference. At the same time, teacher's readings and videos recorded the maximum visitations, followed by completion of topics by the learners, and practice exercises, in that order.

These findings agree with Athani et al. (2017) who point towards the central role of the teacher in the EFL context and firmly establish the fact that the teacher cannot be replaced by e-learning mechanisms. Moreover, the results also show the significance of practice in language learning which the data showed to be correlated with assessment performance.

Learning analytics uses static and dynamic data derived from virtual learning environments. The interactions that take place in the virtual learning environment typically produce this dynamic data. There are numerous ways for grouping data at this moment, but it is still unclear which interactions and groups should be evaluated and examined. There is also disagreement over whether or how these interactions affect student progress, academic achievement, or learning outcomes.

Conclusion

In order to comprehend and improve the learning process, learning analytics uses static and dynamic data derived from virtual learning environments. The interactions that take place in the virtual learning environment typically produce this dynamic data. There are numerous ways for grouping data at this moment, but it is still unclear which interactions and groups should be evaluated and examined. There is also disagreement over whether or how these interactions affect student progress, academic achievement, or learning outcomes. This points towards greater spirit of inquiry into the expansion of LA into the classrooms. Yet, with the greater intervention of technological tools and apps in language learning, the question of predicting learner success came as a natural corollary.

Recommendations

The results of this study have opened new vistas for the effective and optimum use of LA in the language learning class. Here are the recommended Ways to use Learning Analytics in the EFL classroom of KSA:

1. Track the poor performers or the weak students:

With the benefit of giving insight into the learning behavior of each student, teachers can identify students who need different pathways for learning.

2. Track learners' engagement:

Analytics reports can be a great way to track the engagement level of the learners by looking at the time spent on the courseware and identifying areas that needed more time for completion. LA reports can be broken down into which content learners have viewed; for example, how many times they attempted an exercise, and whether they failed or succeeded in doing it, watched a video, or listened to an audio.

3. Lesson customization:

Learning behaviors are a combination of learning strategies and learner aptitudes. Teachers understand that every learner is unique and has a unique set of needs. LA reports can help teachers customize lessons to suit every kind of learner, especially those who are different.

4. Measure and compare learning success:

In conventional classrooms, the only way to measure learners' performance and understanding was by way of assessments without taking into account the quality or nature of the input. Armed with LA reports, however, teachers have access to a 360^{o} view of learners' performance throughout the year.

5. Redesign materials:

LA reports can foresee trends and help teachers predict learning obstacles and redesign materials to suit needs and achieve learning objectives. They can also reassess their pedagogies and make adjustments as and when needed.

Limitations

This study has been a unique attempt at making the most of technology in the EFL classroom. However, the researcher acknowledges certain limitations, though they were beyond his domain. One, the number of learners in the study has been small for a study that dwelt upon big data analytics in education. A large sample would certainly add to the depth of similar future studies. Two, learner feedback on how the application of LA changed their learning experience is an important component as all effort is ultimately directed towards their enrichment. It is hoped that other studies will adopt a mixed methods approach.

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Conflicts of Interest:
It is certified here that there is no conflict of interest, whatsoever.

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