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Data-Based Learning Analysis and Its Application to English Education: Focusing on Online and Blended Learning Environment

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This study uses a portion of the learner data from Learning management system(LMS) to find factors that affect academic achievement. In addition, this study tried to suggest a method to apply this learning analysis to English education. For this purpose, the LMS data for (1) lectures during the 4th semester (September 2020~June 2022) in the 'online class environment' due to COVID-19 and (2) classes in the 2nd semester in 2022 conducted as 'blended learning' classes was collected and analyzed. The main results are as follows. In the 'online learning environment', it was found that there was a significant positive correlation between the access frequency and grades by LMS content and the frequency of access to class lecture videos, notices and assignments had a significant effect on learners' grades. In the 'blended learning environment' the results of the correlation analysis showed that there was a significant positive correlation between the access frequency of announcements and videos and grades. However, in the results of the regression analysis, there were no variables that affected grades. This study is meaningful in that it investigated the relationship between the frequency of access to each content and academic achievement in order to identify more accurate variables.

[data-based learning analysis/online learning/blended learning/English education]

I. INTRODUCTION

Interest in education using information and communication technology (ICT) has accelerated due to technological development in the era of the 4th industrial revolution and

COVID-19, even in English education (Kim, H. Y., 2021; Kim, J. E., 2019; Kim, J. E., 2022). A growing number of studies have revealed that technology and ICT-based learning has a positive effect on learners' active participation and motivation in addition to the direct improvement of learners' English proficiency (Kim & Kim, 2019; Park & Kim, 2019). On the other hand, most studies have focused on proposing methods of utilizing technology in class or verifying the effectiveness of application (Lee, 2020). Recently, despite the increasing number of studies on the use of learning management systems (LMS) in foreign language education (Kolesova, 2015), they are difficult to find in domestic studies.

The usage of LMS has grown significantly over the past few years. In the case of the United States, higher education has mainly used LMS for teaching and learning, and its use is increasing dramatically in Korea as well. Recently, blended learning, which utilizes the advantages of both offline classes and online learning, is gradually expanding and LMS is continuously being used for this purpose (Kim, A. N., 2021; Kim, H. Y., 2021).

Moreover, with the recent development of artificial intelligence-based data analysis techniques and the importance of personalized education, studies on learner behavior analysis and academic achievement prediction using LMS are actively being conducted (Conjin, Snijders, Kleingeld, & Matzat, 2016; Han & Chun, 2015; Hu, Lo, & Shih, 2014; Im & Lee, 2003; Jho, 2018; Jo & Kim, 2013; Kim & Kim, 2011; Kim, 2013; Lee, 2018; Riestra-González, Paule-Ruí, & Ortin, 2021). In particular, early prediction using the data accumulated in the LMS is meaningful in that it prevents students from dropping out and increases the possibility of improving students' academic achievement. To predict academic achievement early in LMS, it is necessary to develop a learning management system using artificial intelligence. For this purpose, it is necessary to collect appropriate learning data and develop a prediction model. Domestically and internationally, many studies on learning analysis or LMS analysis have been conducted in educational technology or other fields, but as mentioned above, there are very few studies related to English learning or education.

Therefore, in this study, some of the learner data of the LMS are used to find out the correlation with academic achievement and to find factors that affect academic achievement. In addition, this study intends to suggest a method that can be applied to English education to increase English subject achievement and help promote English learning.

Looking at previous studies using LMS log data conducted in Korea, most of them have attempted to identify the relationship between behavioral factors, such as regularity of learning start intervals, total learning time, number of accesses to learning, submission of assignments, participation in discussions, and academic achievement (Han & Chun, 2015). However, until now, it is difficult to find studies that consider the type of content accessed by learners. However, in order to identify more accurate variables, this study tried to find out the relationship between the frequency of access and achievement by type of content such as each lecture video, class material and assignment. As the number of contents uploaded by

instructor, semester, and subject is different, as in the previous study, looking only at the number of accesses may reduce its reliability. Therefore, as in this study, how often a student accesses a specific content of a specific course while taking a specific course can provide more meaningful information than simple LMS access frequency or attendance information. In order to design adaptive e-learning learning using artificial intelligence in the future, it will be helpful to access the LMS and see what content and how often.

This study focused on the online and blended learning environment, because in this environment, learning depends on the will of the learner, and the activeness of the learner's participation in learning inevitably affects learning performance (Harasim, Hiltz, Teles, & Turoff, 1995).

The research questions of this study for this purpose are as follows.

1. To what extent does the frequency of access by content affect the prediction of academic achievement in the 'online learning environment'?
2. To what extent does the frequency of access by content affect the prediction of academic achievement in the 'blended learning environment'?
3. What are the suggestions for applying this data-based learning analysis to English education?

II. THEORETICAL BACKGROUND

1. Learning Analytics

It has been argued that individualized learning should be provided in order to maximize the effectiveness of online learning. Recently, attempts have been made to build a more effective learning management system by applying learning analytics, which analyzes students' learning data using big data technology and presents differentiated prescriptions according to the learner's characteristics. According to Macfadyen and Dawson (2012), learning analytics collects and analyzes learning activity data generated during the learning process, finds regularities in the data, predicts class dropout or the degree of achievement based on this, and manages learning outcomes.

Evaluating and managing learners' performance by analyzing learning-related data has been attempted for a long time. In the past, learning analysis was mainly conducted through learner evaluation or questionnaires, and based on this, teaching and learning activities were improved. Meanwhile, recently, educators are trying to improve learners' educational performance by utilizing big data that can be collected in an online environment. In other words, in recent years, learning analytics is often seen as a research method for dividing big

data collected in an online education environment and using the results obtained from such analysis in an educational way.

A representative example of applying learning analytics is Course Signals of Purdue University in the United States. This system provides students with feedback on their performance in the course they are currently taking based on information on their learning activities, providing them with an opportunity to ask for help in advance or make other decisions (Pistilli & Arnold, 2010). The main purpose of learning analysis will be to provide information to instructors and learners to help them make decisions. In addition, through learning analysis, customized educational content for each learner can be provided and the quality of education can be improved (Hu et al., 2014; Viberg, Hatakka, Bälter, & Mavroudi, 2018). This is because it is possible to make prescriptions for learning improvement based on the analysis results or to achieve optimization of learning through evaluation and improvement.

For research on learning analysis, various data such as data collected directly from learners through questionnaires in traditional methods, recently, learning activity data left by students while learning through a learning platform, spatio-temporal data, and physiological psychological data are used. The most commonly used is the data accumulated in the LMS (Schwendimann et al., 2016).

2. Data Analysis of LMS

A LMS is a software application for delivering, documenting, tracking, reporting and managing educational programs. It is also expressed as a collection of e-learning tools available through a shared management interface, including interactive tools including messaging and discussion boards, course materials, assignments, and assessments. In addition, it provides a variety of information to closely review learners' learning process and is continuously being upgraded (Black, Beck, Dawson, Jinks, & DiPietro, 2007; Nichols, 2003; Riestra-González et al., 2021). Information from the LMS was used to create predictive models for a variety of purposes, including predicting student performance and detecting procrastination.

In Korea, research has also been conducted to prevent students from dropping out and improve students' academic achievement by early prediction of academic achievement using data accumulated in LMS. Through this, it was possible to improve academic performance by early identification of students experiencing academic difficulties at the beginning of the semester. Most of the studies related to LMS previously in Korea were studies based on the possibility of completion of remote/cyber universities or studies on predicting academic achievement through data analysis of corporate e-learning students (Han & Chun, 2015; Im & Lee, 2003; Kim & Kim, 2011; Kim, 2013; Lee, 2018). Han and Chun (2015) analyzed the

correlation between LMS log data and academic achievement targeting corporate e-learning workers, and found that simply numerical learning time and learning access frequency do not increase learning performance. Woo, Kim and Bu (2012) analyzed all learning participation activities in the LMS of a cyber university and saw the correlation between grades and course evaluation. As a result, LMS learning participation activity and grades were related, but it was found to be low with lecture evaluation. Recently, these studies are gradually expanding to studies targeting university students, and recently, interest in designing adaptive e-learning based on the learning style, which is the preferred method of each learner, is also increasing (Shariffudin, Julia-Guan, Dayang, Mislan, & Lee, 2012). For example, Rau and Durand (2000) tried to predict the relationship between learning time and grades in LMS and to predict grades. Research on this topic was also done in Korea, and argued that the regularity of learning time intervals can predict academic achievement. Research on the use of LMS dashboards has also been conducted.

III. METHOD

1. Data Collection

For this study, the LMS data for (1) lectures during the 4th semester (September 2020~June 2022) in the 'Online class environment' due to COVID-19 and (2) classes in the 2nd semester in 2022 conducted as 'Blended learning' classes were collected. The data of 12 classes targeting students from 1st to 4th grade of the Department of English Education were included, and among the subjects conducted during the 4th semester, classes mainly conducted as real-time video classes were excluded from the analysis.

By using the mid-point data of the 8th week of the semester instead of the whole semester data, it was found out whether it is possible to predict academic achievement early. The purpose of this study is not just to classify students according to academic achievement, but to create a predictive model, apply the results of this study to English education, and motivate English learners to perform better or initiate necessary interventions early.

Among learner data, the number of accesses to lecture videos, materials, announcements, and assignments, which can be called major contents, and the relationship between these variables with grades (total score), which is the learner's achievement, were investigated. Time management variables commonly included in previous studies on the influence of time management variables on learners are the total learning time or online connection maintenance time and the number of accesses to learning (Macfadyen & Dawson, 2010). However, this time was excluded because learners sometimes leave the LMS open and partake in other activities. In the case of messages, most of the students interacted with

KakaoTalk, which was excluded as well. Test and assignment evaluation scores were also stored on the LMS server, but these variables were also excluded from the analysis because these scores themselves are naturally related to grades. In the online class, access frequency data for 6356 videos, 18474 assignments, 7157 materials, and 2964 notices were collected up to 8 weeks.

The total number of target learners was 305 students enrolled in the Department of English Education, but among them, there were overlapping learners. However, it was not possible to distinguish duplicate learners, because individual identification was made impossible by assigning random identifiers to each student.

In this study, in addition to the online environment, the frequency of content access in the blended learning environment was also analyzed. Classes in the second semester of 2022 were conducted as face-to-face classes, and lecture videos or materials were uploaded to the LMS before face-to-face classes for blended learning. Four classes were targeted, and access frequency data for 1135 videos, 1473 Materials, and 697 Notices were collected for 8 weeks. Since face-to-face classes were conducted concurrently, assignments were not included.

For academic achievement, the total score for each subject was used as an index. The grades of the universities studied consisted of A+, A, B+, B, C+, C, D+, D, and F, but this included not only midterm, final, and assignment grades, but also participation scores and attendance. Therefore, in this study, only the total score, including midterm, final, and assignment scores, which affect only achievement, was used. In addition, the grades of the subject subjects were evaluated by relative evaluation, but this study divided the total score excluding participation score or attendance into three groups: excellent, average, and low achievement.

2. Analysis Method

Based on the collected data, descriptive statistical analysis, correlation analysis, and multiple regression analysis were conducted using SPSS 22. First, the frequency of access to lecture videos, materials, assignments, and notices was investigated, correlation analysis was conducted with grades, and a total score prediction model was constructed by performing multiple regression analysis on the total score. In order to find out whether it was possible to predict the total score by learning analysis until the middle of the semester, data up to 8th week were analyzed. In fact, in a previous study that investigated the point at which scores could be significantly predicted with time management data of LMS during the learner's learning process, it was found that prediction was possible from 4 weeks after the start of classes (Lee & Seo, 2021).

The average number of accesses was calculated by dividing the total number of accesses by the number of each content because the number of lecture videos, uploaded Materials,

assignments, and announcements could vary by semester and subject. The number of lecture videos should be 7 until the 8th week, but in the case of real-time online or face-to-face classes, it became less than 7. In the case of assignments, all elective assignments were counted even if they were not required assignments.

IV. RESULTS

1. Online Learning Environment

1) Descriptive Statistics of Online Learning Environment

Using 34,951 total accesses in online classes from the second semester of 2020 to the 1st semester of 2022, the descriptive statistics value by variable, the number of contents by semester/subject, and the average number of access to content are shown in Tables 1 to 3, respectively. As a result of the analysis, it was found that learners access content several times on average, and in particular, the average access frequency for assignments exceeds 10. This access frequency includes viewing by clicking several times a day and dividing the video into several times by not viewing the entire video at once. It can be seen as interest in multiple accesses, but it can also be interpreted as poor time management, poor concentration, or poor understanding.

TABLE 1
Total Number of Accesses to Content until the 8th Week of Online Environment (*N* = 34951)

	n	*M*	*SD*
Notice	2,964	9.72	6.69
Lecture Video	6,356	20.84	10.81
Materials	7,157	23.47	15.45
Assignment	18,474	60.57	34.56

TABLE 2
Number of Contents per Semester/Subject up to the 8th Week of Online Environment

Semester	Class	Notice	Lecture Video	Materials	Assignment
2020-2	A	5	7	7	7
	B	4	7	7	7
	C	3	7	6	5
2021-1	D	3	7	7	7
	E	1	6	7	5
	F	3	7	7	7
2021-2	G	6	5	7	5
	H	6	6	7	6

	I	7	7	6	7
	J	4	6	6	3
2022-1	K	3	5	6	3
	L	4	7	7	6

TABLE 3
Mean Number of Accesses by Content of Online Environment

	Min	Max	*M*	*SD*
Notice	0.00	16.00	2.50	1.85
Lecture Video	0.00	12.40	3.24	1.69
Materials	0.00	11.14	3.45	2.20
Assignment	0.00	36.67	10.50	5.54

2) Correlation Analysis and Multiple Regression Analysis of Online Learning Environment

A correlation analysis was performed to find out the relationship between the frequency of access and learning outcomes for each content of LMS.

Table 4 shows that there was a significant positive correlation between the access frequency and grades by LMS content. In particular, the correlation coefficient between Total score (grade) and Notice, and between Total score (grade) and Assignment exceeded .4. Based on these results, it can be interpreted that the learners accessed several times out of interest rather than due to poor time management, poor concentration, or poor understanding.

TABLE 4
Correlation Analysis of Online Learning Environment

		Notice	Lecture Video	Materials	Assignment	Total Score (Grade)
Notice	Pearson's correlation coefficient	1	.374**	.160**	.405**	.410**
	Significance level		.000	.005	.000	.000
	n	305	305	305	305	305
Lecture Video	Pearson's correlation coefficient	.374**	1	.131*	.448**	.357**
	SL	.000		.023	.000	.000
	n	305	305	305	305	305
Materials	*Pearson's CC*	.160**	.131*	1	.327**	.193**
	SL	.005	.023		.000	.001
	n	305	305	305	305	305

Assignment	*Pearson's CC*t	.405**	.448**	.327**	1	.421**
	SL	.000	.000	.000		.000
	n	305	305	305	305	305
Total score (grade)	*Pearson's CC*t	.410**	.357**	.193**	.421**	1
	S*SL*	.000	.000	.001	.000	
	n	305	305	305	305	305

** The correlation is significant at the 0.01 level (two-tailed).
* The correlation is significant at the 0.05 level (two-tailed).

Multiple regression analysis was conducted to find out the degree of relevance and the frequency of access to certain contents that could explain learning outcomes (Table 5, 6, & 7). According to the results of the study, it was found that the other variables, except for the frequency of access to Materials, had a significant effect on learners' grades. In some cases, learners only watch the Materials that have been organized before the exam, and it can be interpreted that better learning achievement is possible for students who access more videos with detailed explanations rather than just viewing the Materials.

As a result of the significance test, all variables except for the 'Materials access frequency' variable were significant ($F = 27.187$ $p = .000$). In the case of the Durbin-Watson value, there is no autocorrelation when it is closer to 2, and the autocorrelation can be ignored if the value is usually 1.5 to 2.5, but in this study, the autocorrelation was ignored at 2.079.

On the other hand, the *R* square was .266, which means that the average number of accesses per Notice, Lecture Video, Material, and Assignment can explain 26.6% of the learner's grade, and 73.4% can be explained by other variables.

Therefore, the multiple regression equation except for 'Material' with a significance probability greater than .05 is as follows.

Total score (grade)= .096*Notice +.063*Lecture Video + .030*Assignment

TABLE 5
Multiple Regression Analysis of Online Learning (Environment)

Model	*R*	R^2	*EE*	Stat change				Durbin-Watson
				FC	*df1*	*df2*	*p FC*	
1	.516a	.266	.610	27.187	4	300	.000	2.079

Dependent variable: Total score (grade)

TABLE 6
Multiple Regression Analysis of Online Learning (Analysis of Variance)

Model		*SS*	*df*	*MS*	*F*	*p*
1	Regression analysis	40.497	4	10.124	27.187	.000b
	Residual	111.719	300	.372		
	Sum	152.216	304			

Dependent variable: Total score (grade)

TABLE 7
Multiple Regression Analysis of Online Learning (Coefficient)

Model		Non-standard coefficient		Standard coefficient		
		B	*SE*	*ß*	*t*	*p*
1	(Constant)	1.517	.094		16.179	.000
	Notice	.096	.021	.250	4.491	.000
	Lecture Video	.063	.024	.151	2.660	.008
	Materials	.018	.017	.057	1.095	.275
	Assignment	.030	.008	.233	3.875	.000

Dependent variable: Total score (grade)

2. Blended Learning Environment

1) Descriptive Statistics of Blended Learning Environment

Table 8, table 9, and table 10 show the descriptive statistics by variable, the number of contents by semester/subject, and the mean number of connections by content, using the total number of accesses of 3305 in the blended learning class in the second semester of 2022. As a result of the analysis, it can be seen that the average number of accesses to a content by learners is smaller than that of online classes.

TABLE 8
Total Number of Accesses to Content Until the 8th Week of Blended Learning Environment
(N = 3305)

	n	SUM	*M*	*SD*
Notice	80	697.0	8.71	6.33
Lecture Video	80	1135.0	14.19	7.77
Materials PPT/PDF	80	1473.0	18.41	16.91

TABLE 9
Number of Contents per Semester/Subject up to the 8th Week of Blended Learning Environment

Class	Notice	Lecture Video	Materials
A	5	5	5
B	7	5	3
C	3	5	3
D	8	4	5

TABLE 10
Mean Number of Accesses by Content of Blended Learning Environment

	n	Min	Max	*M*	*SD*
Notice	80	0.00	4.00	1.57	0.89
Lecture Video	80	.40	12.00	2.98	1.78
Materials	80	0.00	9.60	3.01	1.85

2) Correlation Analysis and Multiple Regression Analysis of Blended Learning Environment

Table 11 shows that there is a significant positive correlation between the access frequency of notice and lecture videos and the total score (grade). Multiple regression analysis was conducted to find out the degree of relevance and the frequency of access to content that could explain learning outcomes (Table 12, 13, &14). *R* squared was .118, and *p* was also lower than .05, which was significant. However, as a result of Analysis of variance, it was found that there was no access frequency of content that significantly affected the total score (grade) of the learner. Unlike online classes, it was noticed that the frequency of access to learning content did not have a significant effect in blended learning classes.

TABLE 11
Correlation Analysis of Blended Learning Environment

		Notice	Lecture Video	Materials/PPT/PDF	Total score (grade)
Notice	Pearson's correlation coefficient	1	.250*	.281*	.232*
	Significance level		.025	.012	.038
	n	80	80	80	80
Lecture Video	Pearson's correlation coefficient	.250*	1	.278*	.211
	Significance level	.025		.013	.061
	n	80	80	80	80

Materials PPT/PDF	Pearson's correlation coefficient	.281*	.278*	1	.285*
	Significance level	.012	.013		.010
	n	80	80	80	80
Total score (grade)	Pearson's correlation coefficient	.232*	.211	.285*	1
	Significance level	.038	.061	.010	
	n	80	80	80	80

* The correlation is significant at the 0.05 level (two-tailed).

TABLE 12
Multiple Regression Analysis of Blended Learning Environment (Model Summary)

Model	*R*	*RSD*	*ARS*	*EE*	Stat change					Durbin-Watson
					RSC	*C*	*df1*	*df2*	*pFCe*	
1	.344a	.118	.084	.730	.118	3.403	3	76	.022	1.510

Dependent variable: Total score (grade)

TABLE 13
Multiple Regression Analysis of Blended Learning Environment (Analysis of Variance)

	Model	*SS*	*df*	*MS*	*F*	*p*
1	Regression analysis	5.442	3	1.814	3.403	.022b
	Residual	40.508	76	.533		
	Sum	45.950	79			

Dependent variable: Total score (grade)

TABLE 14
Multiple Regression Analysis of Blended Learning Environment (Coefficient)

	Model	Non-standard coefficient		Standard coefficient		
		B	*SE*	*β*	*t*	*p*
1	(Constant)	1.371	.210		6.517	.000
	Notice	.122	.098	.143	1.253	.214
	Lecture Video	.050	.049	.116	1.014	.314
	MaterialsPPT/PDF	.088	.047	.213	1.851	.068

Dependent variable: Total score (grade)

V. CONCLUSIONS & SUGGESTIONS

This study aimed to find factors that affect academic achievement based on learner data of LMS. In addition, this study tried to suggest a method to apply this learning analysis to English education.

The main results are as follows. In the 'Online learning environment', as a result of correlation analysis, it was found that there was a significant positive correlation between the access frequency and grades by LMS content. According to the results of the multiple regression analysis, it was found that the other variables, except for the frequency of access to Materials, had a significant effect on learners' grades. This is similar to most studies, including the study of Piccoli, Ahmad and Ives (2001), which showed a positive effect on the number of LMS accesses.

On the other hand, the *R* square was .266, which means that the average number of accesses per Notice, Lecture Video, Material, and Assignment can explain 26.6% of the learner's grade, and 73.4% can be explained by other variables. In future studies, it is necessary to conduct research on various variables that can explain the remaining 73.4%, so that learners' achievement can be predicted in advance to prevent dropout or to motivate learners.

In the 'Blended learning environment', the results of the correlation analysis showed that there was a significant positive correlation between the access frequency and grades of announcements and videos. Multiple regression analysis was conducted to find out the degree of relevance and whether the frequency of access to content could explain learning outcomes, and it was found that there was no frequency of access to content that significantly affected learning outcomes. Unlike online classes, it was found that the frequency of access to learning content did not have a significant effect in blended learning classes.

In fact, various online learning programs have been actively developed in English education. Moreover, efforts are recently being made to develop English education programs that enable adaptive learning using artificial intelligence. However, most of them are about learning contents and research on learning methods has not been conducted relatively actively. Therefore, like the LMS analysis in this study, it will be necessary to analyze learners' learning behavior, find out the variables that affect English learning performance, and create a learning performance prediction model based on this. As shown in this study, based on the frequency of access to certain content, learning patterns can be identified in more detail, ways to increase learning motivation can be sought, and ultimately learning outcomes can be improved.

Recently, in English education, education using technology and ICT is required and applied a lot, but nevertheless, there are areas where research has not yet been actively conducted. Technology and ICT-based English learning can directly improve English

learners' English proficiency, but the achievement can be further enhanced through learners' active participation. In order to induce active participation and predict academic achievement in advance, the development of a learning management system using artificial intelligence is required. To this end, it is necessary to collect appropriate learning data and develop a prediction model. In order to improve the achievement of English learning in English education, research on data collection or prediction models for English learners should be actively conducted.

Although this study targeted multiple semesters and multiple subject classes, there is a limit to the data of one instructor's class at one university. Therefore, for generalization, research using data collected from various universities, especially in English classes, should be conducted. Furthermore, since these are not actual English classes, but instead are English education and students' classes, the results may be slightly different. It will also be necessary to compare the results with the results of English classes in the future.

In addition to this, follow-up studies will also need to analyze qualitative differences, not simply considering frequencies. In the case of the underachiever group, each student can show various patterns. For example, although they access content a lot, there is a possibility that they cannot focus on one content or the learning duration is short. For these types of underachieving students, it will be necessary to suggest suitable English learning methods for them.

Despite these limitations, this study is meaningful in that it tries to expand the scope of technology and ICT to English education. In addition, while most studies so far did not consider the type of content accessed by students, this study attempts to find out the relationship between the frequency of access to each content and academic achievement in order to identify more accurate variables. Although many studies on education and learning analysis using LMS are being conducted in the field of 'Educational Technology,' it is necessary to apply more diverse technology and ICT in the field of English education so that English education can lead the education required in the future.

REFERENCES

Black, E. W., Beck, D., Dawson, K., Jinks, S., & DiPietro, M. (2007). The other side of the LMS: Considering implementation and use in the adoption of an LMS in online and blended learning environments. *Tech Trends, 51*(2), 35-53.

Conjin, R., Snijders, C., Kleingeld, A., & Matzat, U. (2016). Predicting student performance from LMS Data: A comparison of 17 blended courses using Moodle LMS. *IEEE Transactions on Learning Technologies, 10*(1), 17-29.

Han, D. H., & Chun, B. J. (2015). Analysis of learning type factors that affect e-learning performance: Centering on the comparison analysis of whole learners log and excellent learners. *Journal of The Korean Data Analysis Society, 17*(2), 897-912.

Harasim, L. M., Hiltz, S. R., Teles, L., & Turoff, M. (1995). *Learning networks; A field guide to teaching and learning online.* Cambridge, MA: MIT.

Hu, Y. H., Lo, C. L., & Shih, S. P. (2014). Developing early warning systems to predict students' online learning performance. *Computers in Human Behavior, 36,* 469-478.

Im, Y. W., & Lee, K. (2003). A study on the dropout problem in Korean online universities: Searching for its solutions. *The Journal of Korean Education, 30*(3), 321-348.

Jho, H. K. (2018). Exploration of predictive model for learning outcomes of students in the e-learning environment by using machine learning. *The Journal of Learner-Centered Curriculum and Instruction, 18*(21), 553-572.

Jo, I. H., & Kim, J. H. (2013). Investigation of statistically significant period for achievement prediction model in e-Learning. *Journal of Educational Technology, 29*(2), 285-306.

Kim, A. N. (2021). Analysis of learner behavior and learning performance using LMS big data in the COVID-19: Focused on J-University. *Korean Association for Learner-Centered Curriculum and Instruction, 21*(6), 565-579.

Kim, H. A., & Kim, H. J. (2011). The study on factors predicting adult learners' academic achievement and persistence in distance education. *Journal of lifelong Learning Society, 7*(3), 51-78.

Kim, H. Y. (2021). The future direction and challenges of English education in the post-COVID-19 era. *English Teaching, 76*(s1), 87-105.

Kim, I. S., & Kim, B. G. (2019). Reforming English learning with interactive artificial intelligence in the era of fourth industrial revolution. *English21, 32*(1), 119-138.

Kim, J. E. (2019). English education majoring students perception of the English education for the fourth industrial revolution era. *English Language & Literature Teaching, 25*(2), 21-38.

Kim, J. E. (2022). Big data analysis of changes in social perception of English education and suggestions for raising awareness about technology-based English education. *English Language & Literature Teaching, 28*(1), 107-121.

Kim, J. H. (2013). Study on the determinants of student drop-out in online universities. *Journal of Cyber Education, 7*(2), 1-16.

Kolesova, T. V. (2015). Conditions of effective use of electronic educational platform Moodle forimproving the quality of independent work of students in teaching a foreign language. *Bulletin of Mariiskii University, 1*(16), 19-22.

Lee, H. (2020). A systematic review of technology and ICT-based English education for middle and high school students in the fourth industrial revolution. *Studies in Foreign Language Education, 34*(1), 87-114.

Lee, H. J. (2018). Study for prediction system of learning achievements of cyber university students using deep learning based on autoencoder. *Journal of Digital Contents Society, 19*(6), 1115-1121.

Lee, J. Y., & Seo, J. T. (2021). Probability of learner's course completion by time management and personal background data in lifelong distance education. *Studies in Foreign Language Education, 21*(8), 365-377.

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), 588-599.

Nichols, M. (2003). A theory for eLearning. *Educational Technology & Society, 6*(2), 1-10.

Park, S. J., & Kim, K. J. (2019). A Study on the effects of mobile app-based grammar learning on college students' grammar ability and their perceptions. *Studies in Foreign Language Education, 33*(2), 301-325.

Piccoli, G., Ahmad, R., & Ives, B. (2001). Web-Based virtual learning environments: A research framework and a preliminary assessment of effectiveness in basic IT skills training. *Management Information Systems Research Center, 25*(4), 40-426.

Pistilli, M. D., & Arnold, K. E. (2010). Purdue Signals: Mining real-time academic data to enhance student success. *About Campus,15*(3), 22-24.

Rau, W., & Durand, A. (2000). The academic ethic and college grades: Does hard work help students to "Make the Grade" ?. *Sociology of Education, 73*(1), 19-38.

Riestra-González, M., Paule-Ruíz, M., & Ortin, F. (2021). Massive LMS log data analysis for the early prediction of course-agnostic student performance. *Computers & Education, 163,* 1-20.

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., & Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30-41.

Shariffudin, R. S., Julia-Guan, C. H., Dayang, T., Mislan, N., & Lee, M. F. (2012). Mobile learning environmentsfor diverse learners in higher education. *International Journal of Future Computer and Communication, 1*(1), 32-35.

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in human behavior, 89,* 98-110.

Woo, J. J., Kim, B. N., & Bu, K. D. (2012). A study on the verification of influential power over learning effect by the learning participation activities: the LMS of the O Cyber University. *Journal of Korean Institute of Information Technology, 10*(4), 97-103.

Examples in: English
Applicable Languages: English
Applicable Levels: Tertiary

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