Open Praxis, vol. 11 issue 2, April–June 2019, pp. 129–141 (ISSN 2304-070X)

OPEN PRAXIS

INTERNATIONAL COUNCIL FOR OPEN AND DISTANCE EDUCATION

How e-learning engagement time affects academic achievement in e-learning environments. A large-scale study of open and distance learners

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Abstract

The literature is considerably rich about engagement and academic achievement in the context of open and distance learning. However, there is limited research that investigates these variables with large scale participants. In this regard, the aim of this research was to investigate causal correlations between e-learning engagement time and academic achievement of open and distance learners according to course subject, dropout, and bounce rate variables. The participants of this study were 323,264 open and distance learners from Anadolu University, Turkey. Throughout this research, open and distance learners' engagement time levels and their academic achievements are compared. Academic achievement was found to increase significantly when learners engaged more with e-learning materials.

Keywords: Open and distance learning; Academic achievement; Engagement time; Bounce rate

Introduction

In e-learning systems, a range of materials are used to facilitate and support students' learning processes. Learners engagement with these materials is essential to provide effective and efficient learning and reach course outcomes. Additionally, as well as learning materials, their engagement on e-learning systems is important to provide learner-content interaction (Moore, 1989) because "student-content interaction can perform some functions of the educational transaction formerly accomplished exclusively through teacher-learner interaction" (Anderson, 2003, p.137). In massive distance education systems, where the engagement with e-learning systems is an indicator for the student-content interaction, it is important to understand it from a broader perspective. In this regard, this study examines the students' achievement on e-learning systems from the perspective of engagement and bounce rate.

Literature Review

Stovall (2003) states that engagement consists of both the time learners spend on tasks and their willingness to take part in activities. Krause and Coates (2008) associate engagement with the high quality in learning outcomes. Engagement requires being active, and having sense making (Harper & Quaye, 2009). The engagement is defined as "the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes" (Astin, 1985, 1993; Pace, 1995; Chickering & Gamson, 1987; Hu & Kuh, 2001).

Reception date: 6 October 2018 • Acceptance date: 15 April 2019
DOI: https://doi.org/10.5944/openpraxis.11.2.920

Bounce rate is the percentage of visitors who enter a site (or a page) and then leave immediately without visiting any other pages. It could also be expressed in terms of time spent on site (e.g., users who spend five seconds or less on the site) irrespective of the number of pages they view. Djamasbi et al. (2014), underline the negative effects of bounce-rate on potential users' engagement in web sites.

Krause and Coates (2008) reports regulated measurement of learner engagement from a large-scale study of first year undergraduate learners in Australian universities. The analysis of the study presents different type of undergraduate learner engagement, including online, self-managed, peer and student-staff engagement. The findings point out the development of a broader understanding of engagement as a process with several dimensions. The study calls for a more robust theorizing of the engagement concept that encompasses both quantitative and qualitative measures. It takes into account the implications for pedagogy and institutional policy in support of enriching the quality of the learner experience.

In Liaw's study (2008), learner satisfaction, behavioral intentions, and the effectiveness of the Blackboard e-learning system is investigated. The results showed that perceived self-efficacy is a critical factor that affects learner satisfaction with the Blackboard e-learning system. Both perceived usefulness and perceived satisfaction support learner behavioral intention to use the e-learning system. In addition, effectiveness of e-learning can be affected by multimedia instruction, interactive learning activities, and e-learning system quality. This study suggests a conceptual model to comprehend learner satisfaction, behavioral intention, and effectiveness of using the e-learning system.

Oye, Iahad, Madar and Rahim's (2012) study examined the application of e-learning model to explain acceptance of the e-learning technology in the academic settings. The study confirmed that in order to foster individuals' intention to use e-learning environments, positive perception on e-learning use is crucial. By using linear regression analysis, the study verified that while attitudes influence intention to use, the actual e-learning use has significant effect on learners' academic performance. In this study, e-learning use is associated with learners' increased academic performance. The study suggested that sessions of training and information on e-learning need to focus primarily on how the e-learning technology improve the efficiency and effectiveness of learners' learning processes.

In their study, Nguyen, Huptych and Rienties (2018) investigated the students' timing of engagement and its relation to learning design and academic performance. The analysis was conducted for about 28 weeks using trace data, on 387 students over two semesters in 2015 and 2016. Students spent less time studying the assigned materials compared to the number of hours recommended by instructors. The timing of engagement also varied from in advance to catching up patterns. High-performing students spent more time studying in advance, while low-performing students spent a higher proportion of their time on catching-up activities. The importance of pedagogical context to transform analytics into actionable insights emphasized in the study. Research results of Tao, Zhang and Lai (2018) show that there is a positive relationship between perceived online learning environment and university students' learning performance driven by student participation. For this reason, educators should develop online student participation strategies to increase online student participation and improve the learning performance of online students.

McKenna and Kopittke (2018) examined the use of lecture notes, lecture slides, and lecture recording utilized by first-year students through the learning management system. In the study, it was stated that lecture slides were downloaded by more students than other learning resources and 71% of students used at least one type of learning resource. Authors stated that distance learners use learning resources (lecture notes and recording) more often than campus students. The learning resources were mostly downloaded during the 13th week, revision week and exam week. In the study, there was no relationship between participation and formative quiz scores while there was a positive relationship between participation and final summative exam scores.

In their study, Zhang, Li, Liu, Cao and Liu, (2019) focused on the data-driven online learning engagement detection via facial expression and mouse behavior recognition technology. To improve the accuracy of learning engagement detection, face data and mouse interaction used as two aspects of students' behavior data. Thus, higher recognition rates received.

Studies about engagement, dropout and academic achievement is rich in the related literature. However, there are limited number of studies which compare these variables with large scale participant numbers from the perspective of open and distance learning. Furthermore, transformation of learners' shifting engagement with the educational environments appears to have radically changed from traditional materials to online environments in the last decades. As a new phenomenon, online engagement is related to individuals' online interactions, session duration and navigation (White & Le Cornu, 2011). Therefore, measuring online engagement with psychological test only is almost impossible in massive online learning environments. For this reason, in order to determine students' interactions; new variables such as number of hits, spent time and, bounce rates should be examined. Thus, engagement time in online learning environments became as an important variable that can used in massive education context and learning analytic studies. It is considered that this study will fulfil the gap in the literature and be a model for future studies.

Purpose of the research

The purpose of this study is to compare open and distance learners' e-learning engagement time (the time spent on e-learning portal) and academic achievement according to course, dropout and bounce rate variables. In this regard, the study intends to shed light to following research questions:

1. Is there a significant difference between learners' engagement time levels depending on courses they study?
2. Is there a significant difference between learners' academic achievement depending on their engagement time levels?
3. Do the engagement time levels significantly predict learners' academic achievement?

Methodology

The structure of this study is a post-test only model. The main purpose of these models is to test descriptive causal hypotheses about causes that could be manipulated (Shadish, Cook & Campbell, 2002). Accordingly, this study searches for causal connections between e-learning engagement time and academic achievement. The research design of this research is summarized in Table 1.

In this research, the causal correlation between engagement time, bounce rate, dropout and academic achievement variables are analyzed. Engagement time represents the time learners

Table 1: Research design.

Group	Procedures	Post-test
A (Bounce Rate)	e-Learning Interaction (URL, Time)	GPA, Engagement Time
B (Average Group)	e-Learning Interaction (URL, Time)	GPA, Engagement Time
C (Advance Group)	e-Learning Interaction (URL, Time)	GPA, Engagement Time
*A=Control Group; B=Experimental Group 1; C=Experimental Group 2		

spend on the web system, bounce rate represents the ratio of learners who stay on the system between 0–99 seconds during a term, dropout represents the learners whose GPAs are 0, academic achievement represents GPA (Grade Point Average) in this study.

Sampling

The participants of this study are chosen randomly from Anadolu University Open Education system. They are the learners who study with e-learning materials (e-books, videos, tests, etc.) of four courses including *Ataturk's Principles and Revolution History I, Basic Concepts of Law, Introduction to Economics I,* and *Basic Information Technologies I*. These courses are chosen because learner populations, the number of learning resources and visit times are greater than other courses. Thus, 323,264 learners' e-learning system usage data is used to carry out statistical analysis.

The courses chosen for the purposes of this study are designed in the same way. Each course is designed in a unit-based format. Each unit includes the associated learning resources. The variety and types of learning materials in each unit of the each course is similar. It should be noted here that the primary difference in course design for the chosen courses is the content presented.

Data collection process

When conducting a research in mega systems such as Anadolu University Open Education System, it is required to study with large-scale samples. In this research, the logs of Anadolu University Open Education System's e-learning portal are recorded during the academic term. Learner data like student IDs, pages visited, timestamps are kept in logs when they were active in the e-learning system. These logs, consisting of millions of rows of data, are simplified by using data classification techniques.

Data analysis

The quantitative data is analyzed by using descriptive statistics such as percentage (%), frequency (f), standard deviation (SD), and mean ($\bar{X}$); in addition to parametric tests such as independent two samples t-test, one-way ANOVA, Pearson correlation coefficient, and simple linear regression analysis. While interpreting analyses results, some supportive statistics such as eta square (η^2) are utilized due to the big volume of the data. Effect size is a statistical value which shows deviation level of the expectations defined in null hypothesis from the results derived from sample (Cohen, 1988; Vache-Haase & Ness, 1999). As effect size is the quantity of the difference between null hypothesis and alternative hypothesis, it is an indicator of practical significance of the results of the research. While statistical significance is affected by sample size, the use of effect size can help to understand the results in more accurate way (Özsoy & Özsoy, 2013). In this manner, when the difference is significant among the groups, eta square (η^2) is used. Calculated eta square values are interpreted according to *Cohen d* index, which is defined as small, medium and big according to .01, .06 and .14 respectively (Büyüköztürk, 2005).

Findings

In this large-scale research, data is obtained from 323,264 learners who registered in Anadolu University Open Education System in fall term of 2015–2016 academic year. Before parametric tests, descriptive statistics of groups and variables are examined. Distribution of the learners according to the courses given in Table 2.

Table 2: Distribution of the learners according to the courses they are registered.

Course	Frequency	Percent
Basic Information Technologies I	79,089	24.5
Basic Concepts of Law	100,880	31.2
Ataturk's Principles and Revolution History I	74,523	23.1
Introduction to Economics I	68,772	21.3
Total	323,264	100.0

As can be seen in Table 2, distribution of the learners according to the courses they are registered in is close to each other. Additionally, it can be seen that on the e-learning portal, learners mostly accessed the e-learning materials of *Basic Concepts of Law* course. Figure 1 shows the distribution of the materials accessed on the e-learning portal according to the courses.

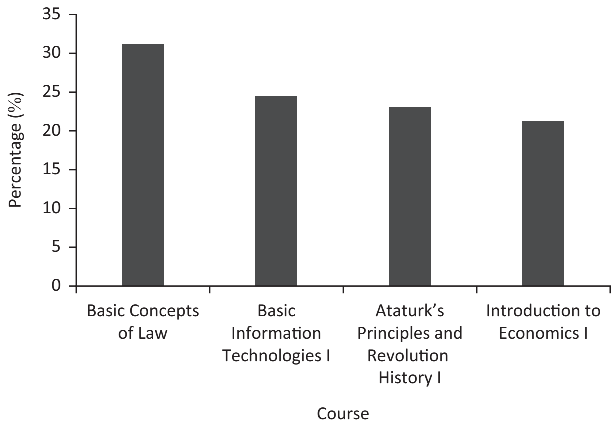

Figure 1: Distribution of the materials accessed (hits) on the e-learning portal according to the courses.

In this study, three groups are obtained by grouping the learners' engagement time level. These groups are bounce rate, average and advance groups. Bounce rate represents the ratio of learners who stay on the system between 0–99 seconds during a term. In the study, learners are grouped as average group that remains in the system between 100 and 999 seconds, and advance group that remains in the system 1000 seconds or more. Distribution of the learners according to these groups is given in Table 3.

Table 3: Distribution of the learners according to their engagement time level.

Engagement	Frequency	Percent
Bounce Rate	90,083	27.9
Average Group	140,790	43.6
Advance Group	92,391	28.6
Total	323,264	100.0

When learners' engagement time on the system is investigated in detail, it is seen that the number of the bounce rate learners and advance group learners is close. For this reason, it can be said that the dropout rate is higher than expected. Distribution of the learners in each group is given in Figure 2.

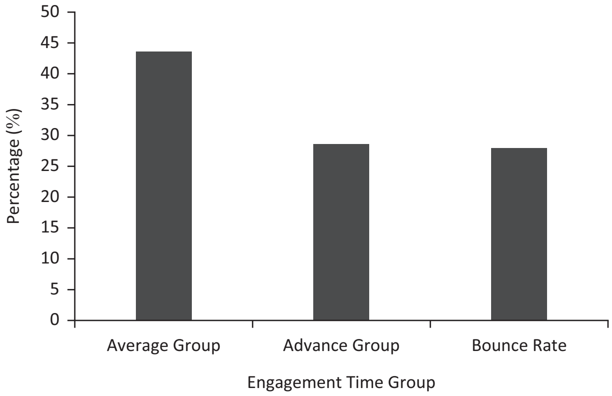

Figure 2: Distribution of the learners in engagement groups.

In this study, in addition to distribution of engagement time groups, two groups generated as dropout and non drop-out learners according to their academic achievement. Distribution of the learners according to this classification is given in Table 4.

Table 4: Distribution of the learners according to their academic achievement.

Types	Frequency	Percent
Dropout	9,793	3.0
Normal	313,471	97.0
Total	323,264	100.0

As can be seen in Table 4, dropout rate is rather low. Learners who dropped without accessing are not included. However, when it is considered that the rate of learners who use the e-learning portal is high, dropout rates of the learners are rather low for this group. In this study, the time learners spent on the e-learning portal according to the courses (second) is analyzed. Results of this analysis is shown in Table 5.

Table 5: The time learners spent on the e-learning portal according to the courses.

Course	Mean (TotalTime- Second)	Mean (TotalTime- Minute)	Std. Deviation (TotalTime- Second)	Std. Deviation (TotalTime-Minute)
Basic Information Technologies I	19738.06	328.97	57004.73	950.08
Basic Concepts of Law	23338.48	388.97	61341.48	1022.358
Ataturk's Principles and Revolution History I	25490.03	424.83	65655.59	1094.26
Introduction to Economics I	21347.24	355.79	57658.06	960.97
Total	22529.99	375.50	60618.95	1010.32

As can be seen in Table 5, the time spent on the e-learning portal differs according to the courses. To define whether this difference is significant or not, one-way ANOVA test is used. Results of one-way ANOVA test are given in Table 6.

Table 6: One-way ANOVA findings of the time spent on the portal according to the courses.

Variables	Groups	df	MS	F	p (two tailed)
Real Time	Between Groups	3	47719809787	130.017	p<.001
	Within Groups	323,260	367026352		
	Total	323,263			

When Table 6 is analyzed, the time spent on the portal according to the courses according to one-way ANOVA findings, it is found that there is difference in .001 significance level [$F_{(3,323263)}$=130.017, p<.001]. Because of the sample size, to define how effective the significant difference is, eta and eta square values are examined. It is found as η=.035, η^2=.0012. According to these findings, it can be said that the significant difference of the time spent on the portal according to the courses has low effect size. Bonferroni test was used to define which groups have significant difference. Post hoc test results are given in Table 7.

Table 7: Post Hoc findings of the time spent on the portal according to the courses.

(I) group	(J) Group	MD (I-J)
Basic Information Technologies I	Basic Concepts of Law	-3600.42034*
	Ataturk's Principles and Revolution History I	-5751.97250*
	Introduction to Economics I	-1609.17921*
Basic Concepts of Law	Basic Information Technologies I	3600.42034*
	Ataturk's Principles and Revolution History I	-2151.55215*
	Introduction to Economics I	1991.24114*
Ataturk's Principles and Revolution History I	Basic Information Technologies I	5751.97250*
	Basic Concepts of Law	2151.5215*
	Introduction to Economics I	4142.79329*
Introduction to Economics I	Basic Information Technologies I	1609.17921*
	Basic Concepts of Law	-1991.24114*
	Ataturk's Principles and Revolution History I	-4142.79329*
Note: * p<.001		

When Table 7 analyzed, Bonferroni post hoc test findings showed difference in .001 significance level among the time spent on the portal according to the courses. Significant difference is defined for all courses. Accordingly, the learners who studied e-learning materials of *Ataturk's Principles and Revolution History I* course, significantly spent more time than the learners who studied e-learning materials of *Basic Concepts of Law* (MD=2151), *Introduction to Economics I* (MD=4142) and *Basic*

Information Technologies I (MD=5751). Besides, the learners who studied e-learning materials of *Basic Concepts of Law* course, spent more significant time than the learners who studied e-learning materials of *Introduction to Economics I* (MD=1991) and *Basic Information Technologies I* (MD=3600) courses. Lastly, the learners who studied e-learning materials of *Introduction to Economics I* course, spent significantly more time than the learners who studied e-learning materials of *Basic Information Technologies I* (MD=1609) course.

In this study, GPA of each student is included with the time learners spent on the e-learning portal. Standard deviation and GPAs of the learners' in the groups obtained at the end of this analysis are given in Table 8.

Table 8: Learners' academic achievement according to the time they spent on the e-learning portal.

Engagement Time Group	Mean (GPA)	Std. Deviation (GPA)
Bounce Rate	37.2658	17.75675
Average Group	39.5740	17.87560
Advance Group	43.8007	17.28946
Total	40.1388	17.85317

As it is seen in Table 8, learners' academic achievement increased as they spent more time on the e-learning portal. One-way ANOVA test is used to define whether the determined differences is statistically significant or not. Findings of one-way ANOVA test of the comparison of academic achievement according to engagement time level are shown in Table 9.

Table 9: One-way ANOVA findings of the comparison of academic achievement according to engagement time level.

Variable	Groups	df	MS	F	p (two tailed)
GPA	Between Groups	2	1013677	3244.123	*p<.001
	Within Groups	323,261	312		
	Total	323,263			

According to one-way ANOVA findings (Table 9), academic achievement according to engagement time level differs in .001 significance level [$F_{(2,323263)}$=3244.123, p<.001]. The effect size was calculated as η=.14, η^2=.02. Despite the fact that obtained effect size value is low, significant difference in the findings has independent impact from sample size. To define among which groups this significant difference comes from, Bonferroni test is used from post hoc tests. Findings of post hoc test are given in Table 10.

According to post hoc test findings, Bonferroni test is used to find among which groups significant difference comes from. These differences are analyzed via one-way ANOVA. According to engagement time groups derived from the time spent on the system, there is a significant difference in terms of learners' academic achievements. It is found that GPAs of advance group learners are significantly higher than both learners in average group (MD=4) and bounce rate group (MD=6). Besides, GPAs of average group learners are significantly higher than the learners in bounce rate group (MD=2). This finding shows that as the engagement time level increased, academic achievement increased significantly. This finding indicates that learners who benefited from e-learning services are more successful.

Table 10: Post Hoc findings about the comparison of academic achievement according to engagement time level groups.

(I) group	(J) Group	MD (I-J)
Bounce Rate	Average Group	-2.30820*
	Advance Group	-6.53486*
Average Group	Bounce Rate	2.30820*
	Advance Group	-4.22665*
Advance Group	Bounce Rate	6.53486*
	Average Group	4.22665*
Note: * p<.001		

Simple linear regression is used to define whether there is a significant difference and correlation between engagement time levels and academic achievement. After simple linear regression analysis, with Pearson correlation analysis there is a significant correlation between engagement time and academic achievement (r=.12, p<.001). Both variables' covariance realized to be significant. Engagement time levels in one term predicts academic achievement with R^2=.015, p<.001 value. Non-standardized regression coefficient is defined as β=39.33, p<.001. Based on these findings, it is possible to assume a causal relation between e-learning engagement time and academic achievement. The regression curve which shows the open and distance learners' engagement time levels and academic achievement covariance is given in Figure 3.

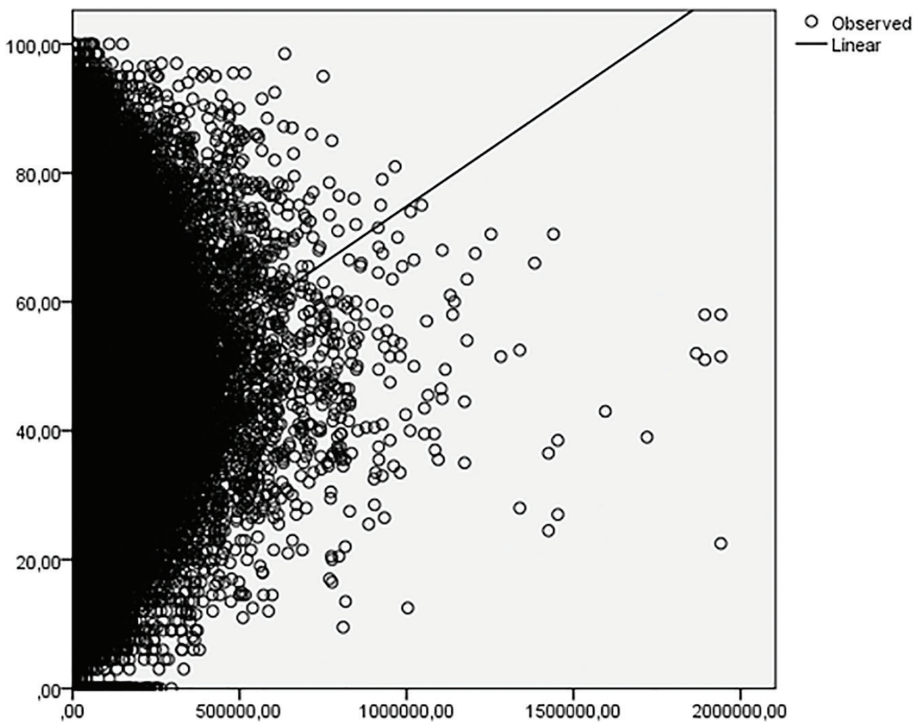

Figure 3: Regression curve of engagement and academic achievement.

When analyzed, it is seen that there are also some other changes besides covariance. Thus, while the open and distance learners' engagement time in one term explains academic achievement until 60 GPA. The highest engagement time is observed in 60 GPA band. After this point, as academic achievement increased, e-learning engagement decreased. It is considered that this remarkable finding needs to be investigated in future studies.

Discussion

There are some remarkable findings to be discussed in this correlation study based on comparisons between two variables. Discussions according to the findings of the data collected from 323,264 open and distance learners during one term are summarized here. Firstly, it is remarkable that the dropout rates of learners are very low and e-learning system bounce rates are high. It is considered that the reason for this is that only the learners who access the e-learning portal are included in this study. Therefore, it is found out that dropout rate is low, bounce rate is high. It is also seen that the learners' engagement time levels according to the courses are differed significantly. It is considered that the main reason of this difference for the benefit of *Ataturk's Principles and Revolution History I* course is the quality, richness and diversity of the materials presented on the e-learning portal. This finding supports Liaw (2008), who reported that "e-learning effectiveness can be influenced by multimedia instruction, interactive learning activities, and e-learning system quality". Thus, e-learning materials of this course can be benefited from as a measure to keep learners on e-learning environments.

One of the main questions of this correlation research is whether academic achievement differs according to e-learning engagement time levels or not. At the end of the parametric tests conducted, it is found out that the more time learners spend on e-learning environment, the more academic achievement they get. Therefore, *bounce rate* group has the lowest GPA while the group which spends more time on the e-learning portal has the highest GPA scores. This finding is in line with Sculley, Malkin, Basu and Bayardo (2009) who found that "a high bounce rate can lead to poor experience" statement. In addition, dropout learners' online time on the system is the lowest, which supports Oye et al. (2012) claims that "active usage of e-learning environments increases academic achievement".

After the regression analysis, which supports the first two research questions findings, it is found out that engagement time level significantly predicts learners' academic achievement when it is calculated by the time they spend in e-learning environment. This finding supports the studies about engagement which increases learning outcomes quality and predicts academic achievement like in Krause and Coates's (2008), Oye et al.'s (2012), and McKenna and Kopittke's (2018) studies. Accordingly, it can be said that open and distance learners' engagement time levels directly affect academic achievement in e-learning environments. For this reason, it can be suggested that measures are needed to be taken to increase learner engagement time in open and distance learning practices.

Conclusion and suggestions

Data collected from 323,264 students of Anadolu University Open Education System in 2015–2016 academic year fall term. Data is collected from the courses with highest enrolment numbers like *Ataturk's Principles and Revolution History I, Basic Concepts of Law, Introduction to Economics I* and *Basic Information Technologies I* between September 2015 and December 2015.

The descriptive statistics revealed that distribution of learners, according to the courses they are registered, is close to each other. Learners' amount of access to e-learning materials according to the courses is *Basic Concepts of Law, Basic Information Technologies I, Ataturk's Principles and Revolution History I* and *Introduction to Economics I*. The number of the learners who use e-learning materials of *Basic Concepts of Law* course is more than the number of the learners of the other courses.

In this research, learners' engagement time was categorized as bounce rate, average, and advance. Almost half of the learners was in average group, the number of learners in advance and bounce rate groups was close to each other. When we consider this result and the number of learners in the studied data set, it can be expressed that learners' dropout rates are low for this group.

One-way ANOVA test carried out to find whether there is a significant difference between the registered courses and engagement time. Significant differences are found between the time spent for each course to the results of ANOVA and post hoc tests. According to this finding, learners who studied e-learning materials of *Ataturk's Principles and Revolution History I*, spent statistically more time than the learners who studied e-learning materials of *Basic Concepts of Law, Introduction to Economics I* and *Basic Information Technologies I.* Additionally, the learners who studied e-learning materials of *Basic Concepts of Law* course, spent more time than the learners who studied e-learning materials of *Introduction to Economics I* and *Basic Information Technologies I*. Similarly, the learners who studied e-learning materials of *Introduction to Economics I* course, spent more time than the learners who studied e-learning materials of *Basic Information Technologies I* course. In conclusion, it is found that the learners spend their time respectively more in *Ataturk's Principles and Revolution History I, Basic Concepts of Law, Introduction to Economics I* and *Basic Information Technologies I* courses.

To define whether time spent on the e-learning portal affects academic achievement one-way ANOVA test is applied. It is determined that the spent time on the system significantly differs according to the academic achievements. At the end of the analyses, it is found out that spend increased time on the e-learning portal, academic achievement increased significantly. This finding shows that the learners who benefited from e-learning services for a longer time became more successful. The advance group, the learners who stayed longer on the system, defined as the most successful group. Accordingly, it shows that the usage of the materials on the e-learning portal affects achievement in a positive way. After the regression analysis which supports this finding, it is realized that the time spend on e-learning environment significantly predicts learners' academic achievement.

Limitations of the study

This research has some limitations, listed as follows:

1. 323,264 learners in 2015–2016 academic year fall term who accessed the online learning portal,
2. Online courses: *Basic Concepts of Law, Basic Information Technologies I, Ataturk's Principles and Revolution History I,* and *Introduction to Economics I* on the e-learning portal,
3. Computer logs kept in fall term of 2015–2016 academic year,
4. GPAs of 323,264 learners who participated the research.

Future implications and suggestions

Based on the findings of this study, the following future implications can be considered:

1. It is considered that organizations who delivers open and distance education may analyze the learners' high bounce rates in e-learning environments to track the engagement of learners and success.

2. Distinguishing characteristics of the e-learning materials of the courses in which the learners spend more time (*Ataturk's Principles and Revolution History I* in this research) can be examined.
3. Since the time spent in e-learning environments affects learners' academic achievement positively, it is considered that researches can be carry out in the institutions to keep learners in the system. For this purpose, gamification factors could be integrated to the system, personalization and enrichment of the learning environment could be suggested.

It is possible to make some suggestions for future research in line with the findings of this research and in the limitations of the study. First, learning analytics can be actively used when studying with big data in open and distance learning. The reason of learners' bounce rates can be questioned through qualitative researches. In addition, complex qualitative and quantitative researches can be conducted to find out why learners are interested more in some courses' e-learning materials (*Ataturk's Principles and Revolution History I* in this research).

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