Journal of Educational Technology &
Online Learning
Volume 5 | Issue 1 | 2022
http://dergipark.org.tr/jetol

E-learning experience: Modeling students' e-learning interactions using log data*

Sinan Keskin [a] **, Halil Yurdugül [b]

[a] Van Yuzuncu Yıl University, Turkey
[b] Hacettepe University, Turkey

Suggested citation: Keskin, S. & Yurdugül H. (2022). E-learning experience: Modeling students' e-learning interactions using log data. *Journal of Educational Technology & Online Learning, 5*(1), 1-13.

Article Info

Keywords:

E-learning
Learner-system interaction
Log data
Interaction pattern

Research Article

Abstract

This study aims to examine e-learning experiences of the learners by using learner system interaction metrics. In this context, an e-learning environment has been structured within the scope of a course. Learners interacted with learning activities and leave various traces when they interact with others, contents, and assessment tasks. Log data were formed on these e-learning interactions. In the data analysis phase, firstly, a data pre-processing was performed, and then confirmatory factor analysis (CFA) was used to test how well the measured learning activity variables represent the latent system component variables. Then it was tested whether these components compose a latent e-learning experience variable (second-order CFA). The results showed that the learners interacted with five different system components: hypertext, the content package, video, discussion, and e-assessment. In conclusion, there is a factorial relationship between the system components and learning activities. These components taken together constitute an e-learning experience variable. When the factor loadings between the e-learning experience structure and subcomponents were examined, the discussion interactions in which the learner structured knowledge highlighted. In summary, the discussions, formative assessments, and content activities formed the learners' e-learning experience together. In order to form a well-structured e-learning environment, these activities together should be experienced by the learners.

1. Introduction

Learning occurs as a result of the interactions of learners in the learning environment. In e-learning, these interactions take place through an online system. Because of the benefits afforded by the technology on which they are built, e-learning environments have made it feasible to conduct learning and teaching activities regardless of time or location. At the same time, monitoring the learning experiences in the learning environment has become possible with these technologies. For this purpose, the log data in which learner behaviors are recorded in e-learning system database can be used to track learning experiences. These data are analyzed using educational data mining techniques and presented as meaningful patterns that explain the learning process (Baker & Yacef, 2009). This study aims to reveal the e-learning experiences of the learners based on the log data.

* This article is based on PhD thesis titled "Determining user profiles for adaptive feedback system design" completed by the first author under the consultancy of the second author.

** Corresponding author. Faculty of Education, Van Yuzuncu Yıl University, Van, Turkey.
e-mail address: sinankeskin@yyu.edu.tr

Doi: https://doi.org/10.31681/jetol.938363
Received 17 May 2021; Revised 2 Nov 2021; Accepted 19 Nov 2021
ISSN: 2618-6586.

E-learning is described as learning activities that take place in virtual settings and are supported by network technologies such as apps and websites (Hrastinski, 2008; Moore et al., 2011). E-learning systems are the environments where e-learning experiences takes place. Open course systems, collaborative learning networks, content management systems (CMS), and learning management systems (LMS) are the most often utilized e-learning platforms today. Even though these systems are referred to with distinct goals and notions, they can all be thought of as integrated web systems that bring together diverse learning activities. In e-learning systems, learning activities and resources are organized weekly or chapter basis. Hypertext pages, online books, asynchronous videos, synchronous meetings, formative online assessments, forums, and wiki pages can be given as the examples of these learning activities and resources. While some LMSs contain all these components and more, some LMSs only contain some of them in line with the instructional design and purpose of the course. E-learning systems store a series of data regarding user-system interactions. These data consist of metrics such as the browsed content types, time spent on different pages, number of clicks, number of e-assessment tasks, user-user (student-student / student-instructor) interactions (Keskin et al., 2019).

Learners leave various traces when they interact with others, contents, and assessment tasks in e-learning contexts. Today, researchers from different disciplines are developing various methods for examining these traces and obtaining meaningful information (Martin & Sherin, 2013). Systems that support decision-making based on such data are becoming widespread day by day in educational institutions. These systems not only promote institutional or individual traceability, but also assist learners in self-assessment and progress (Sampson, 2016). This has led to the emergence of a new research area in which learners' system interactions are examined to obtain meaningful knowledge. This area called educational data mining (EDM) is concerned with the discovery of useful information from the data obtained from educational environments, the development of methods to be used in the information discovery process, and a better understanding of learners and the learning process by using these methods (Baker & Inventado, 2014; Ferguson, 2012). In the early years, EDM started with the analysis of data based on student-system interactions, then continued with research on prediction and relationship mining methods. Although it is a data-driven field, EDM places a strong emphasis on learning and teaching (Ferguson, 2012). The purpose of educational data mining is to organize the existing information in learning and teaching processes in educational communities and to discover useful knowledge from them (Siemens & Baker, 2012). One of the most important factors that make mining important in the educational context is that it handles the measurements and analyzes the individuals involved in the process in their own authentic contexts.

The learners' engagement, use of learning strategies, and time and energy spent in the e-learning environment can all be considered part of the learning experience (Yang et al., 2018). Log records especially contain important information regarding learning experience and learner participation such as time spent, learning strategies, interest level, and individual differences (Christenson et al., 2012; Keskin & Yurdugül, 2019; Schindler et al., 2017). Learning experiences and learner participation have a determining role in teaching and learning performance (Kuh, 2009; Schindler et al., 2017). In this context, EDM guides researchers and practitioners, especially in observing learning experiences and taking necessary precautions in the e-learning process.

In the traditional approach to e-learning design considering a uniform learner profile, the same learning environment is delivered to all learners. On the other hand, each student engaging in the learning environment is unique, and therefore, the student perceives his surroundings and learns in unique ways (Southwell et al., 2007). According to the constructivist learning theory, the individual creates his own personal meaning as a result of interaction. In learning environments based on this theory, learners are presented opportunities to be active, flexible, and responsible for their own learning (Menzi Çetin & Altun, 2014). One of the most important goals of instructional designers is to design learning environments suitable for individual needs. In order to design these environments fitting learner needs, first of all, the design principles should be determined based on the learner and system characteristics. In the process of forming the design principles, adaptive models based on learner characteristics and learning theories provide essential guidance. Accordingly, adaptive learning environments are systems that automatically present personalized options to learners based on a user model that reflects various characteristics of the learner and system (Bra, 1998; Brusilovsky, 1998). In adaptive environments, the system can adapt itself to the characteristics of the individual, considering some parameters belonging to the learners. EDM has an important role in establishing principles or rules for adaptive learning systems.

E-learning experience (usage of resources, interaction intensity, and self-assessment, etc.) metrics can be considered as an important learning performance indicator. For example, there are various studies in the literature suggesting that online engagement is a factor that promotes students' grades and learning (Lee & Rha, 2009; Rodgers, 2008; Nguyen et al., 2018). Besides, the mode of teaching delivery (online, blended, or face to face), learner characteristics (cognitive style, motivation, and readiness, etc.), kinds of teaching activities, and time spent also affect learning outcomes (Keskin & Yurdugül, 2019; Nortvig et al., 2018). For this reason, profiling and modeling studies in online learning will guide researchers and practitioners in data-driven decision-making processes at different levels such as teaching, adaptation, and recommendation. In the e-learning literature, various studies examine sequential behavior patterns (Cheng & Chu, 2019; Şahin et al., 2020), social interactions (Cela et al., 2015; Yıldırım, 2018), learner profiles (Eryılmaz, 2019; Liang, 2017), emotional states (Osmanoğlu et al., 2020), and discussion forum interactions (Huang et al., 2014; Huang et al., 2019; Kent et al., 2016; Wong et al., 2015). In addition to these, studies are carried out to predict students' success (Saa, 2016; Shahiri, & Husain, 2015) or drop out (Baker et al., 2015; Mubarak et al., 2020) using educational data mining techniques. However, there are no modeling studies in which e-learning experiences are examined in terms of learning task components. In this context, this study aimed to create a model for student-component interaction patterns by taking a holistic view of students' e-learning experiences. In this way, the learning tasks that come to the fore in the e-learning and the relationships between these tasks were better presented.

2. Methodology

This research aimed to examine the learners' e-learning experiences on a component basis. Thus, it was possible to evaluate the e-learning experiences under certain components, and then the relations between these components could be revealed. In this context, the learner system interactions were tried to be presented through structural equation modeling. This section introduces the study group, e-learning environment, data collection tools, data collection process, and data analysis methods.

2.1. *Study Group*

The study group of this research consisted of 68 junior pre-service teachers studying at a public university. In this study, the six-week e-learning experiences of the study group were examined. Students who did not participate in the e-learning activities at an adequate level or who distort the data distribution were eliminated from the study group. As a result, a total of 62 students (25 females and 37 males) who actively engaged in the online course activities formed the study group. Participants were studying at the department of Computer Education and Instructional Technology. The study group both had experience and theoretical knowledge about distance education because of the courses they had taken in the previous semesters. At the beginning of the academic year, the information of the students enrolled in the course in which the research data were collected was taken from the student information system and this information was transferred to the e-learning system. Students used the e-learning environment during a semester and interaction log records were recorded. These records, which represent learners' e-learning behaviors, formed the data source of this research.

2.2. *E-Learning Environment Design*

In this research, the course and the contents of this course were decided firstly. Then an interactive e-learning environment was prepared in which the course would be presented. Attention was paid to ensure that the e-learning environment could present different types of e-learning content (video, hyper-text, and audio, etc.). Accordingly, existing learning management systems (LMS) were examined, and Moodle LMS, which is one of the most widely used open source LMSs, was chosen as the e-learning environment. In this study, six-week course materials were prepared. Content, discussion, and assessment activities were created for each chapter in the course. First, content activities such as video, content package (SCORM), and hypertext materials were created. SCORM are packages created according to a set of technical standards. In these packages, interactive e-learning contents such as videos, texts, quizzes can be found together. Afterward, discussion topics were created for the discussion forums. Discussion forums are questioning environments where learners can structure their knowledge. Finally, weekly formative assessment tasks were prepared for the self-assessment. All these preparations were integrated into the LMS environment. In order to increase the usability of the LMS, researchers carried out some visual optimizations. In Figure 1, e-learning materials prepared for a sample chapter are shown.

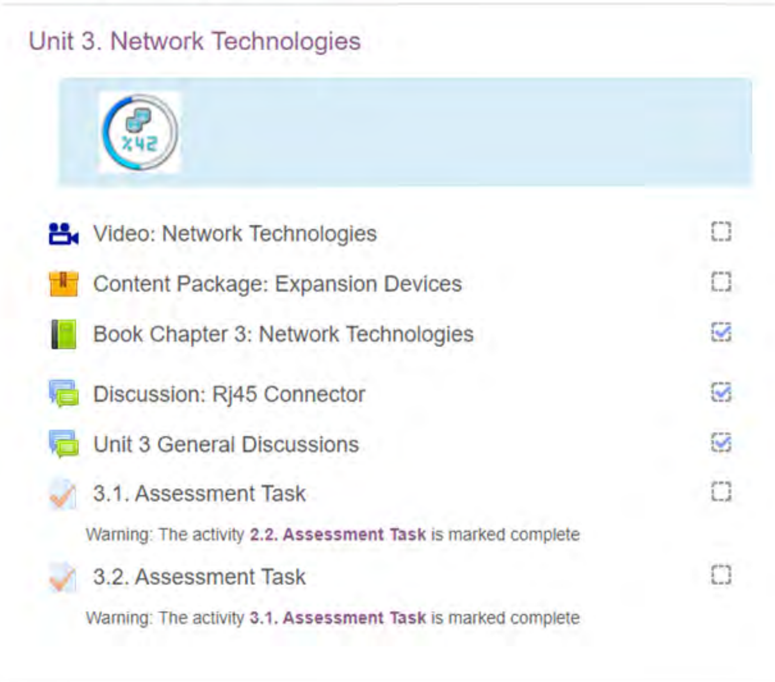

Fig. 1. Online course materials in a sample chapter. (Translated from Turkish)

As seen in Figure 1, content, discussion, and formative assessment materials were presented in line with the chapters' outcomes. Content materials consisted of asynchronous video, hyper-textbook chapters, and content package (SCORM). Instructional discussion pages were created for each chapter so that the learners could discuss with their peers and instructors. Finally, there were formative assessment tasks consisting of multiple-choice items that students can evaluate themselves using the Moodle exam tool. The filled (☑) and empty ( ) boxes next to each learning activity showed whether the learners completed the related tasks. Thus, learners could easily follow the activities they had to complete. Besides, activity completion status was used in restricting access to the consecutive activities. For example, assessment tasks cannot be accessed unless teaching activities are completed. The learners used the e-learning environment for six weeks, and the interaction logs regarding these uses were recorded. These log data representing e-learning experiences constituted the data source of this research.

2.3. *Data Analysis*

Before analyzing the log data, a series of preprocessing operations were performed on the raw data. The first of these operations is the integration of related data stored in the separate tables in the database into a single table. Then outliers and missing observations were determined using normality tests, distribution charts, and these observations were removed from the data set. In the study, confirmatory factor analysis (CFA) was used to examine the relationship between the learning activities and the system components to which these activities belong. CFA was carried out using log data which represents learners' interactions with learning activities. CFA is one of the multivariate statistical methods used to prove predetermined hypothetical relationships between variables and aims to discover new variables conceptually (Harrington, 2009). In addition, the discriminant validity analysis was used to test the construct validity. Using this analysis, the relationships between components were also examined. Finally, a second-order CFA was performed to examine the relationship between the system components and the latent e-learning experience variable.

3. Findings

In this research, e-learning experiences were tried to be presented as an interaction pattern. For this purpose, LMS log data were used. In the LMS database, user interaction logs were stored in two separate data tables. The first of these was Moodle's default learner-system interaction data table. The second one was durations obtained through the AJAX plugin. These raw data from two separate tables were subjected to a data pre-processing. As a result of the data pre-processing, a summary table was created containing the user identity, learning activity, system component, number of access, and duration (in seconds) of the activity. An example section of the summary table obtained from the data preprocessing is presented in Table 1.

Table 1.

The Structure of the Analysis Data Obtained from the Data Pre-processing.

Component / USER ID	Video 2		Assessment 1		…	
	Duration	Access Count	Duration	Access Count	..	..
a	700	9	1066	50	..	..
b	90	1	648	53	..	..
c	801	18	860	65	..	..
d	1097	9	831	50	..	..
e	802	10	1415	80	..	..
..	..	..	..	..	..	..

* The duration was given in seconds.

The rows in Table 1 represent the users, while the columns contain the learning activity, the number of access and the overall interaction time. Before the analysis, a single interaction variable was calculated for each activity. This variable was obtained by dividing the duration by the access count. A data table with 62 rows (62 unique learners) and 23 columns (variables) was obtained after removing the outliers that affected the distribution of the data set.

Based on the learner-system interaction data, a model (Figure 2) was created to examine the relationship between the learning activities and the system components from which these activities were created. While constructing the model, firstly, the latent variables for five basic system components named assessment (assess), hypertext (hypertex), video, content package (scorm), and instructional discussion (forum) were created. Then CFA was used to test how well the measured learning activity (time spent / number of access) variables represent the latent system component variables. The representation of the tested CFA model was given in Figure 2.

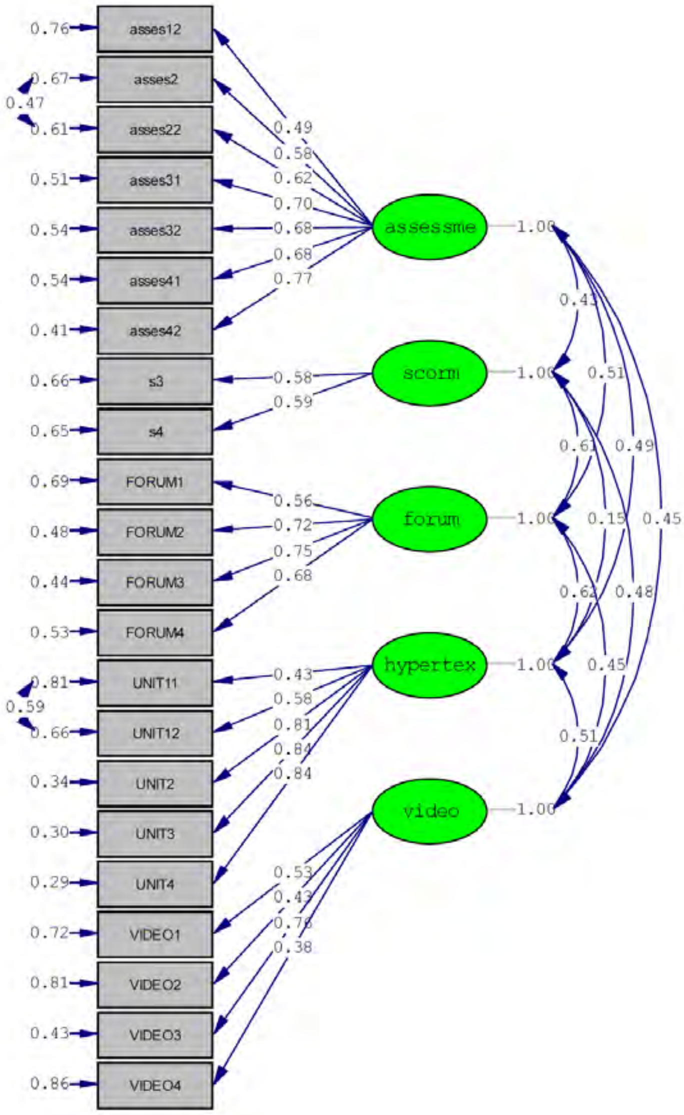

Fig. 2. CFA model for learning activity-component relations with standard coefficients.

First of all, the CFA models' goodness of fit indices were evaluated. As a result of the CFA, the RMSEA was calculated as 0.06, the χ^2/ df as 1.20, the IFI as 0.93, and the S-RMR as 0.09. It was decided that the model had acceptable goodness of fit indices according to these values (Schermelleh-Engel et al., 2003). The parameters obtained from the CFA were given in Table 2.

Table 2.

CFA model parameters.

System Components	Learning Activities	Abbreviation	t	Estimates	β (path coefficients)	R^2
Assessment Tasks	Assessment task 1	assess12	3.77	3.56	0.49	0.24
	Assessment task 2.1	assess2	4.54	6.77	0.58	0.33
	Assessment task 2.2	assess22	5.03	7.22	0.62	0.39
	Assessment task 3.1	assess31	5.82	7.05	0.70	0.49
	Assessment task 3.2	assess32	5.63	6.50	0.68	0.46
	Assessment task 4.1	assess41	5.62	9.91	0.68	0.46
	Assessment task 4.2	assess42	6.57	7.84	0.77	0.59
Scorm (Content package)	Scorm 3	s3	3.66	13.86	0.58	0.34
	Scorm 4	s4	3.69	14.52	0.59	0.35
Discussion forums	Discussion forum 1	FORUM1	4.32	24.46	0.56	0.31

	Discussion forum 2	FORUM2	5.96	27.86	0.72	0.52
	Discussion forum 3	FORUM3	6.24	21.90	0.75	0.56
	Discussion forum 4	FORUM4	5.54	39.17	0.68	0.47
Hypertext books	Chapter 1.1	UNIT11	3.36	12.25	0.43	0.19
	Chapter 1.2	UNIT12	4.73	18.18	0.58	0.34
	Chapter 2	UNIT2	7.35	26.33	0.81	0.66
	Chapter 3	UNIT3	7.68	33.08	0.84	0.70
	Chapter 4	UNIT4	7.74	49.85	0.84	0.71
Videos	Video 1	VIDEO1	3.67	30.72	0.53	0.28
	Video 2	VIDEO2	2.98	60.20	0.43	0.19
	Video 3	VIDEO3	5.20	30.35	0.76	0.57
	Video 4	VIDEO4	2.57	34.73	0.38	0.14

According to the t-test results regarding the factor loadings between learning activities and system components, all factorial relations were statistically significant ($p < .05$). In addition, when these factor loadings were examined one by one, all of them were above 0.30. Accordingly, it is understood that there was a factorial relationship between the system components and learning activities. When the variance explained (R^2) were investigated, it is noteworthy that there was an increasing trend. According to CFA findings, the learner system interactions can be evaluated on a component basis. In other words, interactions with learning activities were significantly gathered under certain components. In order to verify this, discriminant validity analysis, one of the construct validity methods, was used. The findings of discriminant validity analysis were summarized in Table 3.

Table 3.

Correlation Coefficients Between Latent Variables and Square Roots of AVEs.

Factors	AVE	Assessment	SCORM	Forum	Hypertext	Video
Assessment	0.42	0.65*				
SCORM	0.34	0.43	0.59*			
Forum	0.46	0.51	0.61	0.68*		
Hypertext	0.52	0.49	0.15	0.62	0.72*	
Video	0.30	0.45	0.48	0.45	0.51	0.54*

* Above the diagonal elements of the correlation matrix are the square root of AVEs.

In order to satisfy the discriminant validity, the square root values of the AVE (average variance extracted) must be greater than the correlation coefficients between latent variables (Fornell & Larcker, 1981). When Table 3 was examined, it was seen that only the correlation coefficient (0.61) between Forum and SCORM was slightly and ignorable higher than the diagonal value (0.59). Other correlation coefficients were determined to be smaller than the square root of the AVE. Accordingly, the components met the requirements for discriminant validity, and the factors diverge from each other. Since this study was not a scale development research, convergent validity, which is the other component of construct validity, was not tested. Instead, the model-data fit of the hypothesized model was reported in the next step. The second-order CFA was applied to test whether these latent components represent a holistic e-learning experience. For this purpose, a new latent variable named “elearning” was created, and the factorial relation between interaction components and the new e-learning variable was examined. In Figure 3, the standard coefficients and structural model obtained after performing the second-order CFA were given.

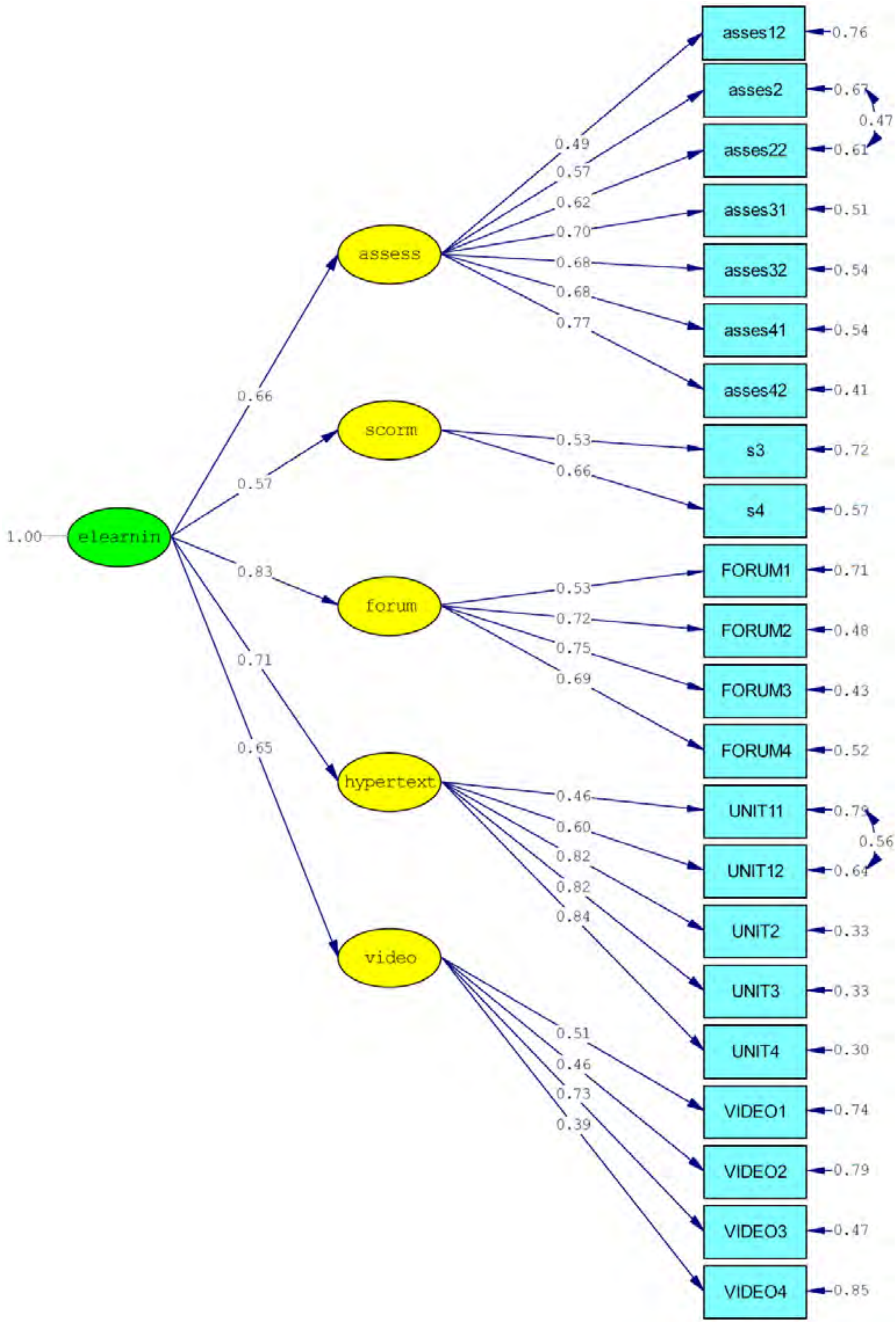

Fig. 3. Results of the second-order CFA with standard coefficients for e-learning experience.

In Figure 3, the second-order CFA model created to test the unification of all e-learning interactions under a superstructure, was given in Figure 3. As a result of the second-order CFA, the RMSEA was calculated as 0.06, χ^2/ df as 1.20, IFI as 0.92, S-RMR as 0.10, CFI as 0.92. The model had acceptable goodness of fit indices according to these values (Schermelleh-Engel et al., 2003). Also, all factorial relations between interaction components and e-learning latent variable were statistically significant according to the t-test (p <0.05). Besides, when these factor loadings were examined one by one, it was seen that all of them were greater than 0.30. Accordingly, the system components discussed in this study aggregated under an exponential e-learning experience factor.

The findings of the CFA revealed that learners' e-learning interactions were grouped into several components, which comprised the e-learning experience together. These components were content interactions (content package, video, and hypertext), discussion, and e-assessment. When the relationships between the components were examined, it was seen that there was a significant moderate positive relationship. It is clear from this finding that e-assessment and asynchronous discussions were also a part of the e-learning experience, just as course contents were. When the factor loadings between e-learning and subcomponents were examined, it was seen that the components were listed as discussion, hypertext, assessment, content package, and video. The results about the importance level of the components showed that the e-assessment experiences (after discussion and hypertext interactions) were also an important interaction experience.

4. Discussion and Conclusion

This research aimed to investigate the e-learning experiences of learners from a holistic perspective. Learner-system interaction data were analyzed for this intent. The learning activity interactions in the e-learning system were associated with the components they were related to, and it was tested whether these components create an e-learning experience. Accordingly, the factorial relationships between learning interactions and the system components to which they belong were investigated. In the e-learning environment, two to seven learning activities were created by using each system component. Research results confirmed that the measured learning activity interactions aggregate under some exponential components. The related learning activities were addressed thematically and named as hypertext, content package, video, discussion, and e-assessment. Accordingly, it was revealed that learners interacted with five different system components in the e-learning environment. In addition, as the learning activities progressed, the variance explained for the related component increased. Although the learning activities in different chapters seem to be independent from each other, learning is a cumulative process built on previously learned knowledge (Shuell, 1988). This cumulative process is also thought to be reflected in the increase of the variance explained.

The second important question addressed in this research was whether these system components represent a holistic e-learning experience. As a result of the study, it was discovered that based on their factor loadings, discussion, hypertext, assessment, content package, and video interactions sequentially constitute a holistic e-learning experience construct. Different e-learning components have roles at different levels in the e-learning experience. As a matter of fact, Huang et al. (2019) revealed that different learning tasks had a significant effect on interaction patterns in terms of depth and diversity. When the factor loadings between the e-learning experience and the components were examined, it was understood that the most important component of the e-learning experience was the instructional discussions, and the least important structure was the content package. When it comes to e-learning design, content design and planning of synchronous lessons come to mind first. With the MOOCs movement, forms of communication, collaboration, and e-assessment design have become more discussed topics in e-learning processes (Conole, 2015; Shukla et al., 2019). The results of this research also revealed that the discussion forums and e-assessment component were an important part of e-learning, supporting the change in paradigm.

The literature on instructional discussion forums has highlighted the relationship between discussion participation and dropout behavior, course engagement, and learning performance (Huang et al., 2014; Huang et al., 2019; Wong et al., 2015). Huang et al. (2014) found that students with high forum participation were more active in lessons and got better grades than other students. Similarly, the importance of self-assessment, peer-assessment, and learning assessment components in qualified e-learning design is widely discussed in the literature (Conole 2013; Ichimura & Suzuki, 2017; Shukla et al., 2019; Yousef et al., 2014). Earl and Katz (2006) discussed formative assessment in two categories as assessment for learning and assessment as learning and stated that these assessment activities directly contribute to students' learning. Similarly, Hwang and Chang (2011) revealed that formative assessments had a positive effect on learners' academic achievement and attitudes toward the learning process. In parallel with these studies, the current research has shown that e-assessment is an important part of e-learning. Govindasamy (2001) stated that one of the pedagogical principles aiming to create an effective e-learning experience was to include e-assessment activities in the learning ecosystem. In short, the results of this research have shown that e-assessment and discussion activities have a complementary role together with content interactions for an effective e-learning experience.

Based on the findings of the current research, several promising future directions for the designing e-learning course design can be suggested. For example, discussion forums and formative assessment tasks seems particularly promising. First, while designing courses for e-learning, discussion forums that provide collaboration and communication between learners should be included. Second, in the context of self-assessment, formative assessments are an important component of the e-learning experience. Online course designs should include e-assessment tasks where learners can test themselves. This research tested whether existing e-learning interactions create a holistic learning experience. The predictability of these interaction components on achievement, satisfaction, dropout rates can be tested in future studies.

References

Baker, R. S., & Yacef, K. (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. *Journal of Educational Data Mining*, *1*(1), 3–17. https://doi.org/10.5281/zenodo.3554657

Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson, & B. White, (Eds.), *Learning analytics* (pp. 61-75). Springer.

Baker, R. S., Lindrum, D., Lindrum, M. J., & Perkowski, D. (2015). *Analyzing early at-risk factors in higher education E-learning courses.* International Educational Data Mining Society. https://files.eric.ed.gov/fulltext/ED560553.pdf Accessed 20 August 2020.

Bra, P. D. (1998) Adaptive Hypermedia on the Web: Methods, techniques and applications. In *Proceedings of the AACE WebNet'98* (pp. 220-225), AACE, Orlando.

Brusilovsky, P. (1998) Methods and techniques of adaptive hypermedia. In P. Brusilovsky, A. Kobsa, J. Vassileva (Eds.), *Adaptive Hypertext and Hypermedia* (pp. 1-44). Kluwer Academic Publishers.

Cela, K. L., Sicilia, M. Á., & Sánchez, S. (2015). Social network analysis in e-learning environments: A preliminary systematic review. *Educational Psychology Review*, *27*(1), 219-246.

Cheng, L. C., & Chu, H. C. (2019). An innovative consensus map-embedded collaborative learning system for ER diagram learning: sequential analysis of students' learning achievements. *Interactive Learning Environments*, *27*(3), 410-425. https://doi.org/10.1080/10494820.2018.1482357

Christenson, S. L., Reschly, A. L., & Wylie, C. (2012). *Handbook of research on student engagement*. Springer US. https://doi.org/10.1007/978-1-4614-2018-7

Conole, G. G. (2013). MOOCs as disruptive technologies: strategies for enhancing the learner experience and quality of MOOCs. *Distance Education Journal*, (39). https://revistas.um.es/red/article/view/234221 Accessed 13 May 2020.

Conole, G. (2015). Designing effective MOOCs. *Educational Media International*, *52*(4), 239-252. https://doi.org/10.1080/09523987.2015.1125989

Eryılmaz, M. (2019). The analysis of student behaviors in virtual learning environments by clustering method. *Journal of Van Yüzüncü Yıl University Faculty of Education, 16*(1), 725-743. http://doi.org/10.23891/efdyyu.2019.139

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5/6), 304-317. https://doi.org/10.1504/IJTEL.2012.051816

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Govindasamy, T. (2001). Successful implementation of e-learning: Pedagogical considerations. *The Internet and Higher Education*, *4*(3-4), 287-299.

Harrington, D. (2009). *Confirmatory factor analysis*. Oxford University Press.

Hrastinski, S. (2008). Asynchronous and synchronous e-learning. *Educause Quarterly*, *31*(4), 51-55.

Huang, J., Dasgupta, A., Ghosh, A., Manning, J., & Sanders, M. (2014, March). Superposter behavior in MOOC forums. In *Proceedings of the first ACM conference on Learning@ scale conference* (pp. 117-126).

Huang, C. Q., Han, Z. M., Li, M. X., Jong, M. S. Y., & Tsai, C. C. (2019). Investigating students' interaction patterns and dynamic learning sentiments in online discussions. *Computers & Education*, *140*, 103589. https://doi.org/10.1016/j.compedu.2019.05.015

Hwang, G. J., & Chang, H. F. (2011). A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students. *Computers & Education*, *56*(4), 1023-1031. https://doi.org/10.1016/j.compedu.2010.12.002

Ichimura, Y., & Suzuki, K. (2017). Dimensions of MOOCs for quality design: analysis and synthesis of the literature. *International Journal for Educational Media and Technology*, *11*(1), 42-49. https://jaems.jp/contents/icomej/vol11/05_Ichimura.pdf

Kent, C., Laslo, E., & Rafaeli, S. (2016). Interactivity in online discussions and learning outcomes. *Computers & Education*, *97*, 116-128. https://doi.org/10.1016/j.compedu.2016.03.002

Keskin, S., Aydın, F., & Yurdugül, H. (2019). The determining of outliers on e-learning data in the context of educational data mining and learning analytics. *Educational Technology Theory and Practice*, *9*(1), 292-309. https://doi.org/10.17943/etku.475149

Keskin, S., & Yurdugül, H. (2019). Factors Affecting Students' Preferences for Online and Blended Learning: Motivational vs. Cognitive. *European Journal of Open, Distance and E-learning*, *22*(2). https://doi.org/10.2478/eurodl-2019-0011

Kuh, G. D. (2009). The national survey of student engagement: Conceptual and empirical foundations. In R. M. Gonyea & G. D. Kuh (Eds.), *New Directions for Institutional Research: No. 141. Using NSSE in institutional research* (pp. 5-20). Jossey-Bass.

Lee, H. J., & Rha, I. (2009). Influence of structure and interaction on student achievement and satisfaction in web-based distance learning. *Journal of Educational Technology & Society*, *12*(4), 372-382.

Liang, K., Zhang, Y., He, Y., Zhou, Y., Tan, W., & Li, X. (2017). Online behavior analysis-based student profile for intelligent E-learning. *Journal of Electrical and Computer Engineering*. https://doi.org/10.1155/2017/9720396

Martin, T., & Sherin, B. (2013). Learning analytics and computational techniques for detecting and evaluating patterns in learning: An introduction to the special issue. *Journal of the Learning Sciences*, *22*(4), 511-520.

Menzi Çetin, N. & Altun, A. (2014). Uyarlanabilir öğrenme ortamları ve bir model önerisi. *Eğitim Teknolojileri Araştırmaları Dergisi*, *5*(3).

Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education*, *14*(2), 129-135. https://doi.org/10.1016/j.iheduc.2010.10.001

Mubarak, A. A., Cao, H., & Zhang, W. (2020). Prediction of students' early dropout based on their interaction logs in online learning environment. *Interactive Learning Environments*, 1-20. https://doi.org/10.1080/10494820.2020.1727529

Nguyen, Q., Huptych, M., & Rienties, B. (2018, March). Linking students' timing of engagement to learning design and academic performance. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 141–150). ACM.

Nortvig, A. M., Petersen, A. K., & Balle, S. H. (2018). A literature review of the factors influencing e-learning and blended learning in relation to learning outcome, student satisfaction and engagement. *Electronic Journal of E-learning*, *16*(1), 46-55. https://files.eric.ed.gov/fulltext/EJ1175336.pdf Accessed 10 May 2021.

Osmanoğlu, U. Ö., Atak, O. N., Çağlar, K., Kayhan, H., & Can, T. C. (2020). Sentiment analysis for distance education course materials: A machine learning approach. *Journal of Educational Technology and Online Learning, 3*(1), 31-48. https://doi.org/10.31681/jetol.663733

Rodgers, T. (2008). Student engagement in the e-learning process and the impact on their grades. *International Journal of Cyber Society and Education*, *1*(2), 143-156.

Saa, A. A. (2016). Educational data mining & students' performance prediction. *International Journal of Advanced Computer Science and Applications*, *7*(5), 212-220.

Sampson, D. (2016). Educational Data Analytics Technologies for Data-Driven Decision Making in Schools. *eLearning Industry*. https://elearningindustry.com/educational-data-analytics-technologies Accessed 20 May 2021.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online, 8*(2), 23-74

Schindler, L. A., Burkholder, G. J., Morad, O. A., & Marsh, C. (2017). Computer-based technology and student engagement: a critical review of the literature. *International Journal of Educational Technology in Higher Education, 14*(25), 1-28. https://doi.org/10.1186/s41239-017-0063-0

Shahiri, A. M., & Husain, W. (2015). A review on predicting student's performance using data mining techniques. *Procedia Computer Science*, *72*, 414-422. https://doi.org/10.1016/j.procs.2015.12.157

Shuell, T J. (1988). The role of the student in learning from instruction. *Contemporary Educational Psychology, 13,* 276-295.

Siemens, G., & Baker, R. S. D. (2012, April). Learning analytics and educational data mining: towards communication and collaboration. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 252-254).

Shukla, N., Sharma, A., & Saggu, A. K. (2019, September). E-assessments and feedback mechanisms in Moocs. In *2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)* (Vol. 1, pp. 1-6). IEEE.

Southwell, B. G., Anghelcev, G., Himelboim, I., & Jones, J. (2007). Translating user control availability into perception: The moderating role of prior experience. *Computers in Human Behavior, 23*(1), pp. 554–563. https://doi.org/10.1016/j.chb.2004.10.025

Şahin, M., Keskin, S., & Yurdugül, H. (2020). Sequential analysis of online learning behaviors according to e-learning readiness. In Isaias, P., Sampson, D., Ifenthaler, D. (Ed.), *Online Teaching and Learning in Higher Education.* Springer.

Wong, J. S., Pursel, B., Divinsky, A., & Jansen, B. J. (2015, March). An analysis of MOOC discussion forum interactions from the most active users. In *International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction* (pp. 452-457). Springer.

Yang, D., Lavonen, M. J., & Niemi, H. (2018). Online learning engagement: Factors and results-evidence from literature. *Themes in eLearning, 11*(1), 1-22. https://files.eric.ed.gov/fulltext/EJ1204753.pdf

Yıldırım, D., (2018*). Interrelated analysis of academic achievement, interaction and navigation patterns of distance education students* [Unpublished doctoral dissertation]. Hacettepe University.

Yousef, A. M. F., Chatti, M. A., Schroeder, U., Wosnitza, M., & Jacobs, H. (2014). MOOCs: A review of the state-of the-art. *In Proceedings* of CSEDU2014, *6th International Conference on Computer Supported Education,* 9- 20. Barcelona, Spain.