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ONLINE LEARNERS' READINESS AND LEARNING INTERACTIONS: A SEQUENTIAL ANALYSIS

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ABSTRACT

An important advantage of e-learning environments is the numerical observation of the learning behaviors of students. The use of e-learning environments by students creates a learner data. From these learner data, the navigation patterns obtained by using educational data mining have a very important place in learning and teaching design. Studies have shown that learners' learning behaviors in online learning environments may vary according to the characteristics of learners. Studies on the differentiation of the navigation patterns according to the psycho-educational characteristics of the learners provide very strong inputs to the design of the learning environment appropriate to the characteristics of the students which is named as adaptive learning environments. According to these inputs, learning environment designs can be developed according to the individual characteristics of the students. Online learners' readiness (OLR) for e-learning is an important psycho-educational structure. The aim of this study is to investigate students' navigations in the e-learning environment according to the level of readiness for e-learning. Lag sequential analysis was used when students' system interactions were analyzed sequentially. According to the results of the analysis, it has been found that the sequential navigation patterns of the students differ according to the OLR structure. The findings of this research are expected to provide important information and suggestions to online learning environment designers.

KEYWORDS

Online Learners' Readiness, Log Data, e-Learning, Lag Sequential Analysis

1. INTRODUCTION

Nowadays, e-learning and distance learning are offered to learners by many educational institutions. E-learning is rapidly being adopted by learners as it has many advantages such as ease of access to the learning environment, convenience to individual pace and flexibility. However, the level of readiness of learners as an important psycho-educational structure for e-learning directly affects the learning process. Online learners' readiness (OLR) is a complex structure that encompasses students' competence in using learning technologies, autonomous learning skills and some affective structures. The most important of the sub-constructs of OLR are self-directed learning, learner control, motivation etc. According to the level of having these skills, learners' online learning behaviors may also differ (which is the hypothesis of this research). If these learning behaviors can be determined in advance, changes can be made in the learning, instructional design and even in the design of the learning environment.

The way in which learners learn in relatively new e-learning environments, the learning behavior patterns that are implemented here, are one of the areas of research that are currently unexplained and curious. Data mining, descriptive statistics, inferential statistics etc. methods are used for determining of behavioral patterns in the e-learning environment. There is significant number of researches which aims to explain the navigational behavior patterns of students according to their personal characteristics (Abdullah, Daffa, Bashmail, Alzahrani, & Sadik, 2015, Keskin, Şahin, Özgür, Yurdugul, 2016).

In the scope of this research, the navigation patterns of the students are studied using sequential analysis. Sequential analyzes were performed according to two different levels of OLR, both low and high. In this study; OLR is addressed in the context of self-directed learning, learner control, motivation towards e-learning. The interaction of the students with the e-learning system is covered under three sub-themes as learner-content, learner-assessment and learner-learner proposed by Moore (1989). The learner-content theme was derived from interactions with written materials, SCORM packages, and videos. The learner-learner theme is based on the interaction data in the forum pages. The interactions with the assessment materials in the e-learning environment are considered as the learner-assessment theme. Interactions with content can be considered as a stage of information acquisition. After this phase, the interaction between the other learners in the forum pages can be named as the constructing knowledge. Finally, the interaction with assessment the can be said to be the reflection phase of the e-learning.

1.1 Lag Sequential Analysis

Lag sequential analysis (LSA) (Bakeman & Gottman, 1997) is one of the widely used methods to reveal the consecutive model of human behavior and communication patterns. Consecutive analyzes have emerged, considering that sequential and conditional examination of behavioral probabilities will provide more information rather than simple probabilities. Because in sequential measurements, results of measurements are not independent of each other. Subsequent measurements are influenced by the results of previous measurements (Gottman, & Roy, 1990).

In lag sequential analysis, firstly, a transitional frequency matrix, which shows the transitions between the behaviors, is created. Transition probabilities are calculated using matrix values. The Z-statistics are used to test the significance of transitions between behaviors. The following formula is used in the calculation of the Z score (Bakeman, 1991). The Z score is calculated by using the conditional probabilities which we express as the transition probabilities of the behaviors. If the z score greater than 1.96, we can say that transition is significant at the 0.05 significance level.

$$z = \frac{f_{rc} - f_r p_c}{\sqrt{f_r p_c (1-p_c)(1-p_r)}} \text{ (Bakeman, 1991)}$$

2. METHOD

The aim of this study is to investigate students' navigations in the e-learning environment according to the level of readiness for e-learning. Lag sequential analysis was used when students' system interactions were analyzed sequentially. Log and self-report data were used in the research. The data sources are explained in detail in the next subtitle.

2.1 Data Collection

The log records used in this study were collected from learners who had a 16-week learning experience at Moodle LMS. Self-report was obtained using "undergraduate students' e-learning readiness scale" developed by Demir and Yurdugül (2016). The scale form was rated on a 7-point likert type. Self-directed learning, learner control, motivation sub-dimensions were used in this study. The research also deals with learning approaches that are closely related to autonomous learning. "Biggs' Revised Two Factor Learning Approaches Scale" was used for gathering data about learning approaches. The scale was developed by Biggs, Kember and Leung (2001) and adapted to Turkish by West, Tetik and Gürpınar (2010). The scale is structured in the 5-point likert type.

2.2 E-Learning Environment Design

Moodle LMS was used as e-learning environment in the research. 59 students participated in the research and students had a 16-week learning experience in the e-learning environment. Students interact with the content, discussion and assessment tasks in the system. The learner-content theme was derived from interactions with written materials, SCORM packages, and videos. The learner-learner theme is based on the interaction data in the forum pages. Students interact with their friends and teachers on the forum pages. The interactions with the assessment materials in the e-learning environment are considered as the learner-assessment theme. The system has assessment tasks that are configured separately for each course chapter.

3. FINDINGS

Each of the psycho-educational structures was handled separately and sequential analyzes related to them were carried out. In this section, the transitional frequency matrix and sequential patterns related to the sequential navigations of the students are given. Firstly, in Table 1 transitional probability matrices for OLR structures are given.

Table 1. Transitional probability matrices for OLR structures

High Self Directed				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.64	0.19	0.17	0.49
Discussion (D)	0.47	0.41	0.13	0.18
Assessment (A)	0.27	0.07	0.67	0.33
Total	0.49	0.19	0.33	1.00

Low Self Directed				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.59	0.13	0.28	0.48
Discussion (D)	0.56	0.28	0.17	0.11
Assessment (A)	0.31	0.04	0.65	0.41
Total	0.47	0.11	0.42	1.00

High Learner Control				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.62	0.19	0.19	0.47
Discussion (D)	0.51	0.35	0.14	0.17
Assessment (A)	0.27	0.06	0.67	0.35
Total	0.48	0.17	0.35	1.00

Low Learner Control				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.61	0.14	0.26	0.50
Discussion (D)	0.52	0.31	0.18	0.12
Assessment (A)	0.31	0.05	0.64	0.39
Total	0.48	0.12	0.40	1.00

High Motivation Towards E-Learning				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.58	0.16	0.25	0.47
Discussion (D)	0.47	0.37	0.16	0.15
Assessment (A)	0.33	0.06	0.61	0.38
Total	0.47	0.16	0.37	1.00

Low Motivation Towards E-Learning				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.63	0.18	0.18	0.46
Discussion (D)	0.51	0.34	0.15	0.16
Assessment (A)	0.22	0.05	0.74	0.38
Total	0.46	0.16	0.39	1.00

This research also examined the learning approaches of the students which are highly related to the sub-structures of online readiness. Students' learning approaches are dealt with in two categories as deep and surface approach. Transitional probability matrices for learning approaches is presented in Table 2.

Table 2. Transitional probability matrices for deep and surface learning approaches

Deep Approach				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.66	0.18	0.16	0.51
Discussion (D)	0.49	0.40	0.11	0.18
Assessment (A)	0.26	0.07	0.67	0.31
Total	0.50	0.19	0.31	1.00

Surface Approach				
Frequency	*C*	*D*	*A*	*Total*
Content (C)	0.63	0.18	0.18	0.46
Discussion (D)	0.51	0.34	0.15	0.16
Assessment (A)	0.22	0.05	0.74	0.38
Total	0.46	0.16	0.39	1.00

The statistical significance of the transitions in the sequential navigations of the students was examined by calculating the z-score. As a result of these calculations, statistically significant patterns are presented based on psycho-educational characteristics. In this section, only statistically significant transitions are present. Firstly, sub-dimensions of OLR are discussed. The results of the lag sequential analysis were then studied according to the learning approach of the students.

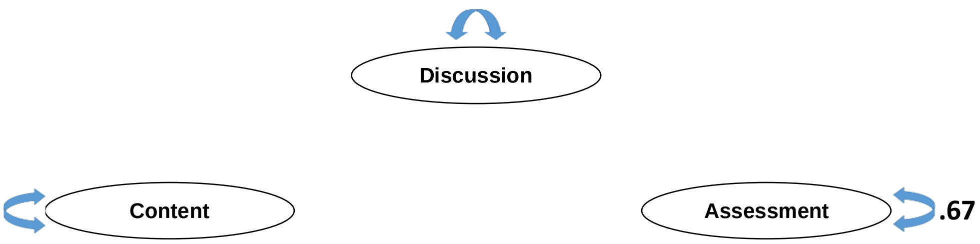

Figure 1. High-level self-directed learner group results

As can be seen in Figure 1, it is possible to say that the students in the high-level self-directed learner group have a persistent navigation pattern. While there was no significant transition between all three themes, the themes seemed to provide statistically significant loop within themselves. The cyclical transition was found to be significant P^{tr}=0.64 in content (z=13.00; p<.05), P^{tr}=0.41 in discussion (z=11.32; p<.05) and P^{tr}=0.67 in assesment (z = 21.65; p <.05).

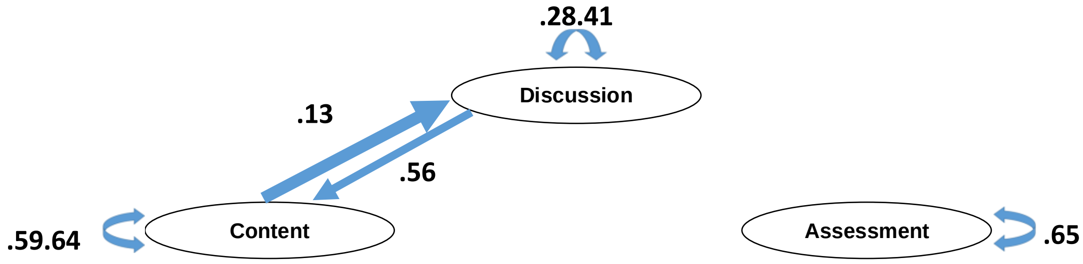

Figure 2. Low-level self-directed learner group results

As can be seen in Figure 2, it is possible to say that the students in the low-level self-directed learner group have a transitional pattern between the themes. The cyclical transition was found to be significant P^{tr}=0.59 in content (z=9.78; p<.05), P^{tr}=0.28 in discussion (z=11.73; p<.05) and P^{tr}=0.65 in assessment (z = 17.75; p <.05). Besides, for low-level self-directed learner group, the transitions from content to discussion (P^{tr}=0.13, z = 3.21) and discussion to content (P^{tr}=0.56, z = 2.51) was found to be statistically significant.

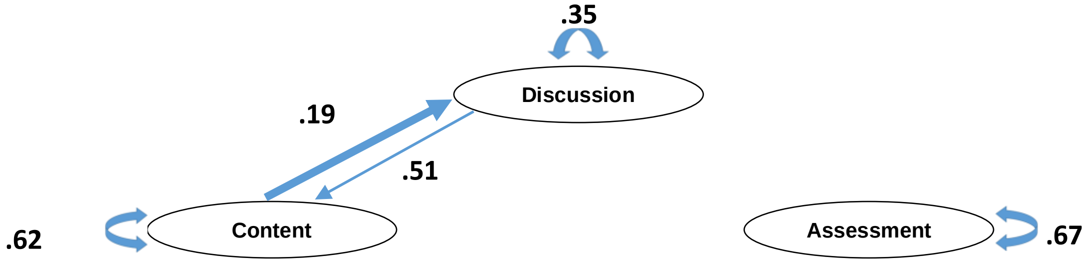

Figure 3. High-level learner control group results

As can be seen in Figure 3, it is possible to say that the students in the high-level learner control group have a transitional pattern between the themes. The cyclical transition was found to be significant P^{tr}=0.62 in content (z=15.29; p<.05), P^{tr}=0.35 in discussion (z=12.21; p<.05) and P^{tr}=0.67 in assessment (z = 28.07; p <.05). Besides, for high-level learner control group, the transitions from content to discussion (P^{tr}=0.19, z = 2.53) was found to be statistically significant. It was determined that there was a transition from discussion to content at a significance level of 0.10.

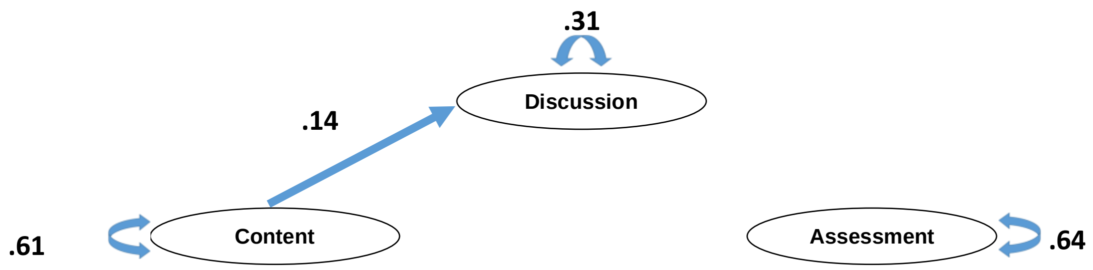

Figure 4. Low-level learner control group results

As can be seen in Figure 4, it is possible to say that the students in the low-level learner control group have a transitional pattern between the themes. The cyclical transition was found to be significant P^{tr}=0.61 in content (z=12.65; p<.05), P^{tr}=0.31 in discussion (z=10.52; p<.05) and P^{tr}=0.64 in assessment (z = 20.25; p <.05). Besides, for low-level learner control group, the transitions from content to discussion (P^{tr}=0.14, z = 2.35) was found to be statistically significant.

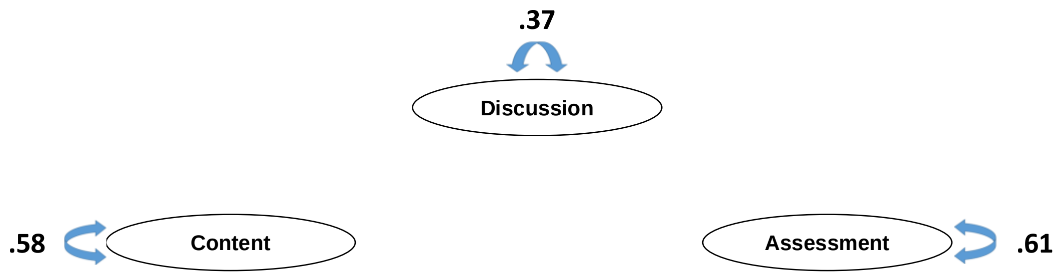

Figure 5. Navigational patterns of students with high motivation towards e-learning

In Figure 5, navigational patterns of students with high motivation towards e-learning was given. Accordingly, it can be said that there is a persistent navigational pattern. While there was no significant transition between all three themes, the themes seemed to provide statistically significant loop within themselves. The cyclical transition was found to be significant P^{tr}=0.58 in content (z=9.78; p<.05), P^{tr}=0.37 in discussion (z=11.73; p<.05) and P^{tr}=0.61 in assessment (z = 17.75; p <.05).

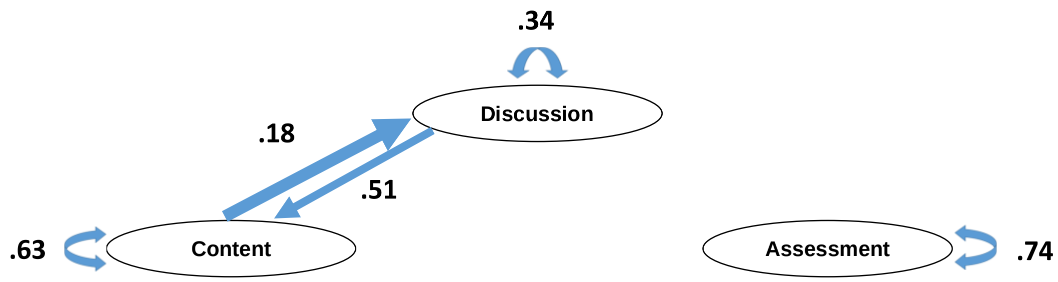

Figure 6. Navigational patterns of students with low motivation towards e-learning

In Figure 6, navigational patterns of students with low motivation towards e-learning was given. Accordingly, it can be said that there is a transitional pattern between the themes. While there was only two significant transition between content and discussion theme, the themes seemed to provide statistically significant loop within themselves. The cyclical transition was found to be P^{tr}=0.63 in content (z=15.65; p<.05), P^{tr}=0.34 in discussion (z=10.50; p<.05) and P^{tr}=0.38 in assessment (z = 26.52; p <.05).

In addition to OLR, sequential navigations based on students' learning approaches have been examined in this research. Findings according to students' learning approaches are presented in Figures 7 and 8.

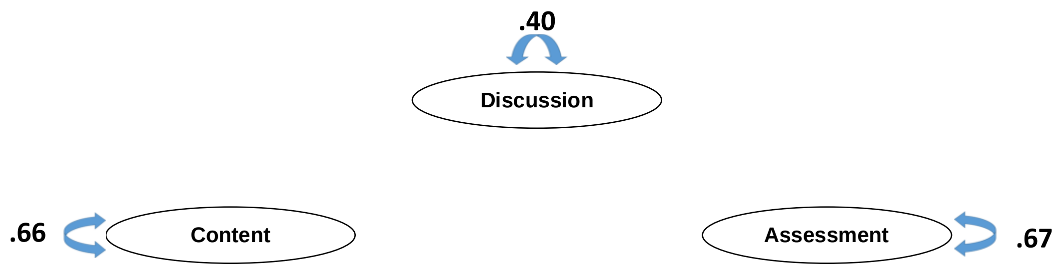

Figure 7. Navigational patterns of students with deep learning approach towards e-learning

When we examine navigational patterns of students with deep learning approach, it is seen that only cyclic transitions are statistically significant (Figure 7). The cyclical transition was found to be significant P^{tr}=0.67 in content (z=13.88; p<.05), P^{tr}=0.40 in discussion (z=11.55; p<.05) and P^{tr}=0.41 in assessment (z = 23.40; p <.05).

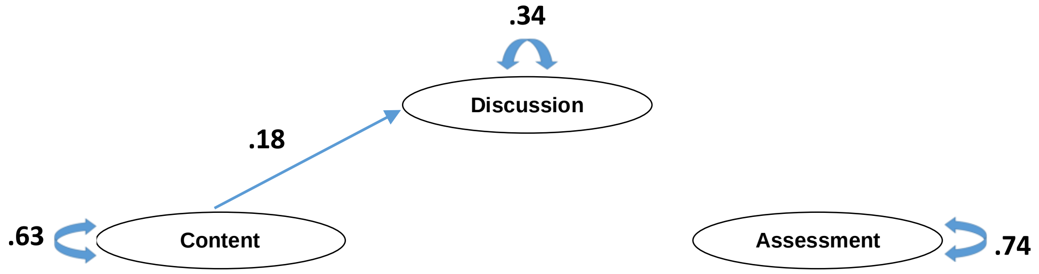

Figure 8. Navigational patterns of students with surface learning approach towards e-learning

In Figure 8, navigational patterns of students with surface learning approach towards e-learning was given. Accordingly, it can be said that there is a transitional pattern between the themes. The cyclical transition was found to be significant P^{tr}=0.57 in content (z=9.54; p<.05), P^{tr}=0.33 in discussion (z=9.17; p<.05) and P^{tr}=0.64 in assessment (z = 16.88; p <.05). Besides, for students with surface learning approach, the transitions from content to discussion (P^{tr}=0.17, z = 3.24) was found to be statistically significant.

4. CONCLUSION

In this study, OLR and the learners' navigation (interaction) sequences in e-learning environments are examined. According to findings, students who have high levels of self-directed learning, learning control, and learning motivation tend to have a consistent interaction in interaction types. On the other hand, it has been observed that students who have these psycho-educational structures low level prefer non-persistent interaction rather than persistent interaction. These students' interactions with content and other themes were intertwine. Because the behaviors expected by students in an LMS environment respectively; a) knowledge acquisition via interaction with content, b) knowledge construct via interaction with learner and finally c) reflection and examining themselves via interaction with assessment. Another pattern observed in the findings is students' interactions were intertwining that have low-level psycho-educational structures. This situation reveals that students need mentoring and scaffolding in e-learning environments.

Readiness is perhaps the first step in learning. Readiness consists two basic skills. One of these is the using instructional technology (computer using, internet using) and the other is autonomous learning skills. Students with high self-directed learning and motivation levels, which are considered to be autonomous learning skills, are consistent in online interactions, while those who are at low levels are more likely to cross between themes. According to this, it can be said that these learners are weak about online learning skills. Because these students have continuously transitioned to discussion and to content without completing a learning task. The behavior of these students was observed to be deep-learner behaviors because of the high level of readiness is typical of deep learning behavior. The instruction designer and environment designer should consider this study and this type study's finding.

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