ONLINE LEARNERS' NAVIGATIONAL PATTERNS BASED ON DATA MINING IN TERMS OF LEARNING ACHIEVEMENT

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ABSTRACT

The aim of this study is to determine navigational patterns of university students in a learning management system (LMS). It also investigates whether online learners' navigational behaviors differ in terms of their academic achievement (pass, fail). The data for the study comes from 65 third grade students enrolled in online Computer Network and Communication lesson in a state university. As the online learning environment, Moodle, an open source software, is used in this study. Navigational log records derived from database were converted into sequential database format. According to students' achievement (pass, failure) at the end of the academic term, these data were divided in two tables. Page connections of the users were transformed into interaction themes namely, homepage, content, discussion, messaging, profile, assessment, feedback and ask the instructor. Data transformed to sequential patterns by the researchers were organized in navigational pattern graphics by taking frequency and ratio into consideration. To test the difference between obtained patterns ratio test was conducted by means of z statistics. The findings of the research revealed that first and second order navigational patterns of passed and failed students in the online learning environment had similar features, but passed students allocated more time to interaction process.

KEYWORDS

Navigational pattern, data mining, online learner

1. INTRODUCTION

With the spread of ICT, its usage in the educational contexts has become prevalent. Especially by the virtue of Web 2.0 technologies, there has been significant progress in the user-system interaction. The principal aim of these technologies is to support learners' learning process and increase their learning performance (Richey, Silber, & Ely, 2008). Web technologies draw attention especially in terms of providing opportunities for time and place independent learning, supporting learners anywhere and anytime, updating teaching materials instantly, having an adaptive nature in accordance with learners' needs (Ally, 2008). Although they offer various advantages, it has been well accounted that self-directed students make better use of these technologies (Grow, 1991; Demir, Yasar, Sert, & Yurdugul, 2014). This fact can be interpreted in such a way that online learning environments may be disadvantageous for those individuals differing from each other in terms of features such as readiness toward online learning, self-directed learning and motivation. With the help of intelligent, adaptive and personalized learning environments, these disadvantages can be minimized through providing feedback and interventions appropriate for individual needs.

The commonly accepted definition of the term interaction is mutual events that's requires two or more interrelated objects and actions (Wagner, 1994). Interaction occurs when these objects and actions influence of each other. Therefore, interaction occurs not only among individuals but also among objects. Accordingly, Moore (1989) states that learning activities present three different interaction types, which are between I) learning and content, II) learner and teacher III) learner and learner. Today, the learning environments are not only in the form of face-to-face classroom settings but also in the form of online platforms. During their experiences in the online learning environment, the users leave traces in relation to their interactions. Recently, researchers from different disciplines have developed methods to analyze and interpret these traces (Martin & Sherin, 2013). Learning analytics refers to the analysis of interactions of learners in the online learning environment and the interpretations of these analyses to have a better understanding of the learning environment and to improve it, which includes the measurement of the data, gathering and analysis it, and reporting the findings (Siemens & Long, 2011; Ferguson 2012). The aim of learning analytics is organizing existing information and explore meaningful knowledge in learning communities' and instruction processes.

Students' having interaction with the learning environment and activities has a positive effect on completing learning tasks (Ma, Han, Yang, & Cheng, 2015). One of the methods to empower and increase that interaction is to recreate learning environments in accordance with the individual characteristics and needs. Teaching content, methods and media should be in consonant with learners' characteristics to get the best benefit from learning environment (Rezaei, & Katz, 2004). To put it another way, providing learners with instructional technology applications is not sufficient to ensure an efficient learning climate. These environments presented to learners must be also suited to individual characteristics. Numerous online learning and evaluation environments are constructed to serve various purposes. Learners navigation behaviors in this environment also varies according to various individual characteristics. Cognitive styles (Chen, & Ford, 1998; Chen, 2010; Ford, & Chen, 2000), gender (Roy, & Chi, 2003), ethnic groups (Lu, Yu, & Liu, 2003); experience (Roy, & Chi, 2003), prior knowledge (Rezende, & Souza Barros, 2008) can be given as examples for these individual characteristics. These differences observed in the navigational patterns not only effect learners' learning performance but also give important recommendations about what kind of personalization and adaptation should be for more efficient and effective learning environment.

In literature there are many studies related to learners' interaction behaviors and navigation patterns. In Chen's (2010) study, a web-based learning system is offered to 105 undergraduate students. Navigational behaviors of the students are detected through log records in system. The results of the study show that students who have different cognitive styles exhibit similar behaviors in linear learning approach, but students make use of different navigation tools in accordance with their cognitive styles. Rezende and Souza Barros, (2008) investigate navigational patterns in terms of learners' prior knowledge. Their study reveals that there is a different navigational patterns for learners according to different prior knowledge. Those who have more prior knowledge have more systematic and organized behaviors and those who have less prior knowledge display less organized behaviors; in other words, their navigation behaviors indicate that they lost their way in the system. In the study conducted by Puntambekar and Stylianou (2005), learners' navigation behaviors in a multimedia setting is examined to provide them different learning support. Students have four different types of navigation in learning system. It has been proved that giving support according to their navigational behaviors, has a positive impact on learners' achievement.

Interactions of learners in an online learning environment are derived from log records and they are expressed as navigation. The aim of the current study is to investigate navigational patterns of university students in a learning management system. Having a close review of the literature, it has been found that there is a research gap in the relation between online learners' navigational patterns and their learning performance. To fill the void, the study aims to examine whether there is a potential difference in navigational patterns of the learners in terms of their academic achievement (pass, fail).

template is a set of styles and page layout settings that determine the appearance of a document. This template matches the printer settings that will be used in the proceeding and the CD-Rom. Use of the template is mandatory.

2. METHOD

2.1 Participants

This study, aiming at investigating navigational patterns of learners in a LMS, draws on the data collected from 65 university students, who registered to Computer Networks and Communication class in a state university.

2.2 Online Learning Environment

As the online learning environment, Moodle, an open source software, is used in this study. Moodle which has a serial database keeps the record of users' all interaction with the system. Moodle was arranged in accordance with the objectives of the class and weekly course content and assessment activities were reconstructed by the lecturer. Within the context of the course, the functions of Moodle such as providing learning content, discussion, messaging, assessment, feedback, profile and schedule were utilized. Learners used LMS for a class period and log records in regard to this usage were kept in the database. Navigational patterns of the learners while using these tools were categorized under 8 themes by the researchers namely, homepage, content, discussion, messaging, profile, assessment, feedback and ask the instructor.

2.3 Data Evaluation

Moodle records the data based on LMS user interaction sequentially in the database. Navigational log records derived from database were converted into sequential database format. In the following table, information related to users' login id, user name, date, time, link of the visited page and duration spent on the page are presented. According to students' achievement (pass, failure) at the end of the academic term, these data were divided in two tables. Afterwards, the tables were reorganized to show how long each user spent time on which internet pages sequentially in a single login. With the available data, 437 alternate logins in relation to passed and 227 alternate logins with regard to failed students were found. Page connections of the users were transformed into interaction themes namely, homepage, content, discussion, messaging, profile, assessment, feedback and ask the instructor. After the processes mentioned above were carried out, the data, as presented in Figure 1, were made prepared to be analyzed. Users differed from each other in terms of the number of navigational steps and time they spent on the system in every unique login. The present study investigates the patterns users follow in the first four steps with regard to system interaction. Additionally, sequential navigations in the same theme were merged.

Sira	ID	session	date	theme1	time1	theme2	time2	theme3	time3	theme4	time4	theme5	time5
32	23392	1RMDZ1j6c	4.03.14	HOMEPAGE	41	CONTENT	7	HOMEPAGI	14	CONTENT	4829	ASSESMEN'	1890
3	517	0939N8Pap	15.03.14	HOMEPAGE	185	ASSESMEN'	6	HOMEPAGI	5	CONTENT	326	ASSESMEN'	948
667	34134	wtDQ8S75J	10.03.14	HOMEPAGE	8	FORUM	8	CONTENT	5	HOMEPAGI	6	CONTENT	934
318	21181	hMa3NMC	2.03.14	HOMEPAGE	13	DONUT	12	HOMEPAGI	13	PROFIL	21	CONTENT	847
181	31611	blFvnQ3k6	9.03.14	HOMEPAGE	7	CONTENT	1103	ASSESMEN'	652	CONTENT	10	ASSESMEN'	792
247	29665	DxylaUe2JE	8.03.14	HOMEPAGE	65	CONTENT	127	PROFIL	26	HOMEPAGI	13	CONTENT	781
392	19206	KJaqVmHM	28.02.14	HOMEPAGE	18	CONTENT	2105	ASSESMEN'	454	CONTENT	29	ASSESMEN'	756
257	38290	Ekv3bfG9JC	12.03.14	HOMEPAGE	29	CONTENT	51	HOMEPAGI	56	CONTENT	352	ASSESMEN'	706
310	39685	h0EYciovYu	13.03.14	HOMEPAGE	5	CONTENT	10	HOMEPAGI	7	FORUM	29	CONTENT	611
241	1520	dQKqCSum	16.03.14	HOMEPAGE	55	ASSESMEN'	75	HOMEPAGI	16	CONTENT	194	ASSESMEN'	581
496	20935	PVYDHgX6s	2.03.14	HOMEPAGE	12	CONTENT	7	FORUM	213	CONTENT	848	ASSESMEN'	517
209	34497	chJfvxnHVv	10.03.14	HOMEPAGE	64	CONTENT	2643	ASSESMEN'	1596	HOMEPAGI	57	FORUM	474
250	15847	e71eZwjFai	26.02.14	HOMEPAGE	10	CONTENT	32	FORUM	212	HOMEPAGI	179	CONTENT	464
210	17311	CHqmd8Bn	27.02.14	HOMEPAGE	22	ASSESMEN'	7	HOMEPAGI	6	CONTENT	267	ASSESMEN'	427
365	22905	JiCBW00UH	3.03.14	HOMEPAGE	14	ASSESMEN'	8	HOMEPAGI	16	CONTENT	320	ASSESMEN'	365
703	20771	xvI9EYfC72	2.03.14	HOMEPAGE	44	CONTENT	165	HOMEPAGI	13	CONTENT	223	FORUM	271
601	3111	ttGLkWJ9z(	17.03.14	HOMEPAGE	23	CONTENT	146	HOMEPAGI	21	ASSESMEN'	7	CONTENT	231
457	25880	nXo80Lc2vl	5.03.14	HOMEPAGE	24	CONTENT	258	HOMEPAGI	5	CONTENT	911	FORUM	209
527	15023	R7RXBcQzD	26.02.14	HOMEPAGE	40	EGITMENE_	8	FORUM	8	PROFIL	7	FORUM	150
661	30225	WLtzXuoTY	8.03.14	HOMEPAGE	18	CONTENT	1090	HOMEPAGI	5	ASSESMEN'	601	CONTENT	127
740	17192	z4HtscePyL	27.02.14	HOMEPAGE	33	CONTENT	285	ASSESMEN'	272	CONTENT	56	ASSESMEN'	97
416	23911	lMK4wynBt	4.03.14	HOMEPAGE	39	CONTENT	698	ASSESMEN'	286	CONTENT	24	ASSESMEN'	88

Figure 1. Sample data table

Data transformed to sequential patterns by the researchers were organized in navigational pattern graphics by taking frequency and ratio into consideration. To test the difference between obtained patterns ratio test was conducted by means of z statistics. The steps of the process follow as such: a) In the first order analysis, frequencies related to which themes login students tend towards afterwards were detected and index values were obtained by dividing the frequencies into total number of logins in each system (passed -failed students). b) Later on, students' tendency towards the second order navigations after each theme in the first order was computed using index values based on frequencies again.

3. FINDINGS

Within the scope of the research, navigational patterns of students who passed and failed the course were revealed. Patterns were examined in first order and second order navigations. These patterns are presented with the ratios in Figure 2.

First and second order navigational patterns of online students and index values based on login frequencies are displayed in Figure 2. It has been shown that in both achievement groups the primary preference of online learners is to form an interaction with the content and later have an interaction with other students in discussion. Therefore, within the scope of the current study, second order navigations are limited to merely navigations after content and discussion. Passed students after having content interaction (excluding those for homepage and log out) tended towards discussion or assessment in the second order navigations. Passed students preferring discussion in the first order navigations opted for content interaction in the second order navigations. While ranking determined a cutpoint by the researchers. This cutpoint is %10.

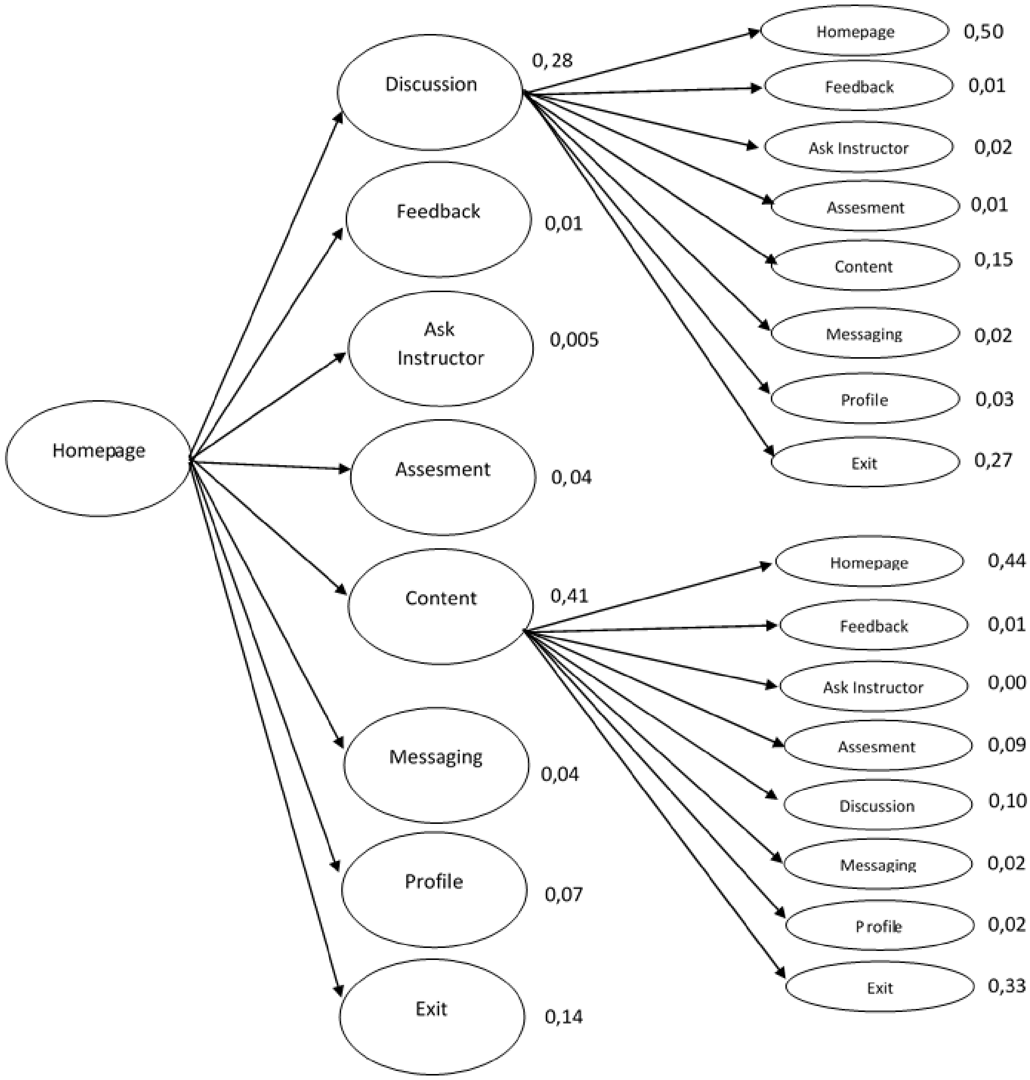

Figure 2 a. Online navigational patterns of passed students

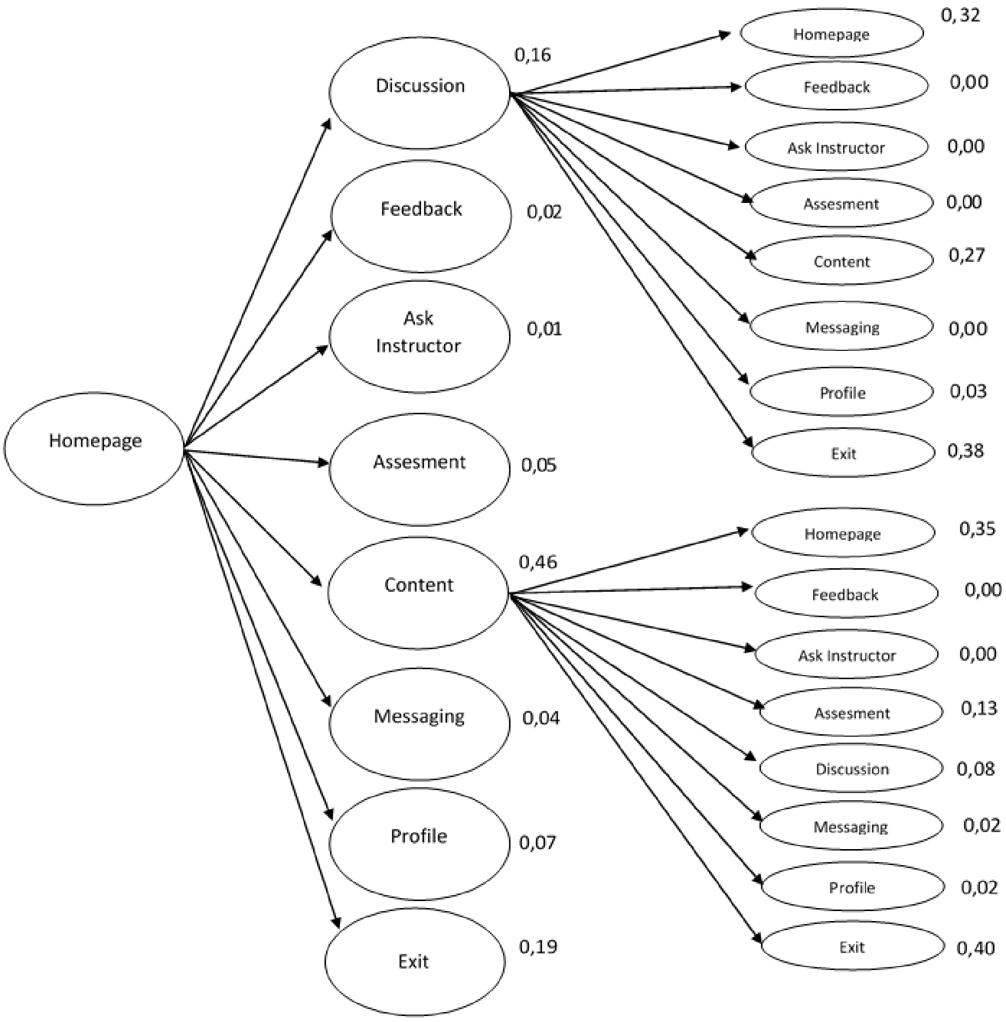

Figure 2 b. Online navigational patterns of failed students

As you can see figure 2.a and 2.b figures numbers represent percentages. For example 28 percent of the passed students link from homepage to discussion page. For the failed students this percentage is 16.

In addition to this, it has been revealed that passed students logged in more and had more content interaction in comparison to failed students. In accordance with students' academic achievement, themes and length of time spent were also investigated. Average times (seconds) of students spent on the pages in the second order and differences are presented in Table 1.

Table 1. Times (Seconds) of learners spent on the page in the second order

	Content	**Discussion**	**Messaging**	**Profile**	**Assessment**	**Feedback**	**Ask Instructor**
Passed	588,24	102,16	30,89	39,84	303,47	16,67	31
Failed	495,25	109,35	9,25	30,40	614	22,60	6,67
Differences	92,99	-7,19	21,64	9,44	242,47	-5,93	24,33

The average time learners spent on second order themes and the difference between passed and failed students are displayed in Table 1. Considering the length of time learners allocated for each theme, it has been shown that when compared to failed students, passed students spent more time on the themes of content, messaging, profile and ask the instructor while failed students allocated more time to discussion, assessment and feedback themes. This finding may be interpreted in such a way that failed students might find the assessment activities demanding and challenging as more time was spent on the part of them. As can be seen from the navigational patterns in Figure 2, there is not a navigational difference between passed and failed students and in both achievement groups, content and discussion interactions are prioritized in the first order navigation. Of the two interactions, content is more crucial and passed students spend more intense time on content interaction in comparison to their counterparts.

4. RESULTS

The results of the current study revealed the navigational patterns of learners in LMS. The research also showed that whether navigational patterns differ or not in terms of academic achievement of the learners. Navigational patterns were handled as first order and second order and whether there was a significant difference between these patterns according to students learning achievement was investigated. Z-test statistic was employed to detect the difference. According to results of the test, no significant difference was found between passed and failed students. Both passed and failed students are mostly visit content and discussion pages in the first order navigation. Additionally, whether there was a difference between the time learners allocated for each login in terms of their academic achievement was examined. The findings showed that there were differences between the passed and failed students with regard to time spent on each login. The study yielded a general result that first and second order navigational patterns of passed and failed students in the online learning environment had similar features but passed students allocated more time each pages in the learning environments.

5. RECOMMENDATION

The current study investigates the navigational patterns of online learners in terms of their achievement. The findings of the research may have a potential for the design of intelligent tutorial systems. According to characteristics and navigations of the learners, intelligent tutorial systems involve intervention and adaptive mechanisms. In the light of the results of the study, although learners differ in terms of their achievement, they draw upon similar ways in the online learning environments but they differentiate in the sense of time they allocate for interaction. Accordingly, especially for those who perform poor in the school the interactions of the learners with the system can be enriched with online learning agents and the interventional feedback suitable for interaction period. So learners can be directed to deep learning.

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