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Application of Access-Log Analysis and Social-Network Analysis to the Study of Foreign-Language Learning

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Abstract

This report presents a new quantitative research method of investigating the English-learning behavior of students in a Web-based learning environment. Studies of computer-assisted language learning and their transition from classroom- to Web-based practices testify to the wide use of Web-based technologies. However, to the best of the author's knowledge, no accessible and practical methods have been identified that investigate the Web-based learning behavior of students. To address this need, this study performs and tests a new quantitative research method that combines access-log analysis and social-network analysis. To investigate the efficacy of the proposed research method, a Web-based learning environment was designed and integrated into in-class lessons. The in-class lessons were held once a week for a period of one and a half months, and 16 university students participated. Their access-log data on the Web-based learning environment were collected and analyzed, which allowed their learning patterns to be identified. In addition, their use of the Web-based materials was visualized to aid in understanding the topology of the Web-based learning environment. The results are used to determine the efficacy of the proposed research method.

Keywords: access-log analysis, social-network analysis, visualization, student learning behavior

1. Introduction

Studies of computer-assisted language learning (CALL) have been experiencing a transitional shift through three stages. According to Warschauer and Healey (1998), CALL research has developed from drill-based "structural CALL" via communication-based "communicative CALL" and finally to content-based "integrative CALL." In addition, Warschauer and Healey noted the importance of incorporating the use of technology into actual teaching practices. From a different viewpoint, Bax (2003) pointed out the significance of developing an integrated practice that puts students at the center and enables tutors and students to use technologies for foreign-language teaching and learning in a natural educational environment.

Influenced by the aforementioned transition, new perspectives on CALL research are emerging. Egbert (2005) reexamined the definition of CALL and stated "CALL means learners learning language in any context with, through, and around computer technologies" (p. 4). Similarly, Kern (2006) claimed to broaden the relationships between computer technologies and language learning and said:

> In sum, the complexity of the issues involved in technology and language learning is pushing us to look beyond gross decontextualized measures of effectiveness to understand effectiveness in terms of the specifics of what people do with computers, how they do it, what it means to them. (p. 189)[1]

From a technological viewpoint, the advancement of research on CALL has allowed Web-based technologies such as learning-management systems (hereafter LMSs) or contents-management systems (hereafter CMSs) to be considered as integration tools. The advantage of using such Web-based technologies is that they allow tutors to supplement in-class instruction and to incorporate student self-learning into classroom activities (Kung & Chuo, 2002; Sumi & Takeuchi, 2010). For example, van Deusen-Scholl, Frei, and Dixon (2005) identified the advantage of using online resources, stating:

> One in-class activity determines its continuation online, and the online activity determines the following in-class activity. This cycling—or spiraling—builds the foundation for on-going reflection of language production and complexity. (p. 664)

Similarly, Levy and Kennedy (2004) employed Web-based audio-conferencing tools as a means of speaking in the target language outside scheduled class time. In recent years, Stickler and Hample (2010) provided a Moodle-based intensive online German course, and Sumi and Takeuchi (2010) conducted blended learning practices using an LMS in junior high school and university environments.

However, these practices that use Web-based technologies to achieve integration seem to have devoted insufficient attention to one important and essential issue that has emerged from recent CALL studies regarding student learning behavior: namely, *how do students use learning materials provided on the Web and how do they learn foreign languages on the Web?* This problem is also clearly mentioned in Stockwell (2007), who used a mobile-based environment for vocabulary learning and said that "there is still very little research that looks at how learners themselves use and perceive mobile language learning activities" (p. 366).

This limitation might result from the inexistence of accessible and practical methods for researchers to obtain data pertaining to student learning behavior on the Web. Consequently, most practices that advocate foreign-language learning via Web-based technologies have inevitably employed existing research methods to validate the efficacy of such practices. Examples of such methods include language tests, questionnaires, classroom observation, and interviews. However, this type of research has no access to data pertaining to the use of Web-based learning materials and how students learn foreign language via the Web. To address this issue, the current study presents a new quantitative research method that combines access-log analysis and social-network analysis to investigate student English-learning behavior in a Web-based learning environment.

The combination of access-log analysis and social-network analysis is a well-known research method in studies of computer-supported collaborative learning and it allows researchers to explore potential relationships among students or remarks (Martinez, Dimitriadis, Rubia-Avi, Gomez-Sanchez, & de la Fuente, 2003; Nurmela, Lehtinen, & Palonen, 1999). However, rare are studies that use access-log analysis or social-network analysis in CALL studies.[2] Two examples of such studies are Stockwell (2007), who collected student access-log data through their use of mobile phones for vocabulary learning, and Laghos and Zaphiris (2007), who collected student remarks on the Web and used social-network analysis to analyze computer-mediated communication in an e-learning environment. However, a holistic and systematic way of applying the combination of access-log analysis and social-network analysis has yet to be clearly identified and fully tested in CALL studies. Therefore, the following research questions will be addressed in this study:

1. *Is the use of the combination of access-log analysis and social-network analysis effective in investigating student learning behavior in a Web-based learning environment?*

2. *What kinds of student learning behavior can be identified with the use of the combination of access-log analysis and social-network analysis?*

2. Access-Log Analysis and Social-Network Analysis

Access-log analysis consists of acquiring and analyzing data on the successive actions on Web users, such as searching, visiting, moving between Web sites, and clicking on content or links. The actions of these Web users are automatically stored in a Web server as data, which can be analyzed with a variety of access-log analysis tools. In general, access-log analysis is used to optimize Web content or design for commercial purposes, but the possibility of applying access-log analysis has been growing in the domain of education (Endo, Kumagai, Kato, Shikoda, & Sasaki, 2009; Kanazawa, Nakayama, & Yamamoto, 2008).

Social-network analysis is based on network theory, which is a branch of modern sociology (de Noory, Mrvar, & Batagelj, 2005). It views any social phenomena as a consequence of the mutual relationship between actors (Yasuda, 2001). In this sense, the purpose of social-network analysis is to investigate the structure and pattern of social relationships between the members of a particular community.

In social-network analysis, nodes or vertexes represent actors or organizations and edges or links represent their mutual relationships. These elements are used to understand the structure of the network in a given community and may be illustrated in graphical form. For example, Figure 1 shows a quasi-personal network (graph G) relating five actors in a community. Each actor (*node*) is labeled (A, B, C, D, and E), and each line (*edge*) is labeled (L_1, L_2, L_3, L_4, and L_5).

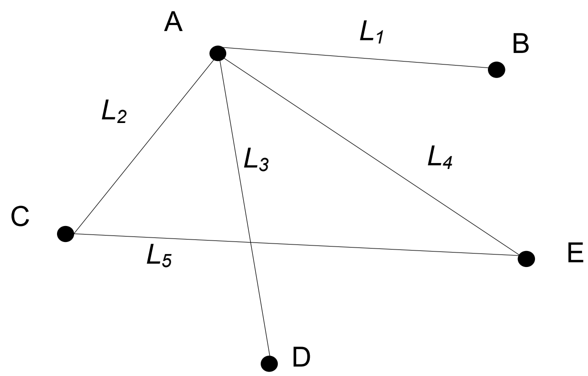

Figure 1. Quasi-personal network. In the context of social-network analysis, such a graph is called sociogram.

The data displays in Figure 1 can be represented as shown below because the graph G contains five nodes N and edges E, and each edge joins two nodes:

$$G = \{N, E\}$$
$$N = \{A, B, C, D, E\}$$
$$E = \{L_1, L_2, L_3, L_4, L_5\}$$
$$E = \{(A, B), (A, C), (A, D), (A, E), (B, A), (C, A), (C, E), (D, A), (E, A), (E, C)\}$$

The network of actors in Figure 1 ($G = \{N, E\}$) may also be represented in matrix form. For Figure 1, there are the same numbers of nodes in rows as there are in columns, so the matrix is square, as shown below (a). This matrix represents the relationships between the nodes and is called an adjacency matrix. In such an adjacency matrix, an element is unity when an edge is recognized (e.g., $E_{AB} = \{A, B\}, \{B, A\}$), which means a relationship exists between the two corresponding nodes. When no edge exists between two nodes no relationship exists, and the corresponding element is zero.

$$\text{adjacency matrix} = \begin{array}{c} \\ A \\ B \\ C \\ D \\ E \end{array} \begin{array}{c} \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{pmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \end{pmatrix} \end{array} \qquad \text{(a)}$$

Another example of a quasi-personal network may be three actors in a community who use four different learning materials. Each actor is labeled (A, B, and C) and each material is labeled (M_1, M_2, M_3, and M_4). The relationship between the actors and materials may be illustrated in a bipartite graph (see Figure 2). The feature of a bipartite graph is to arrange different data sets on opposite sides of the graph, and there is no direct relationship within a single data set (i.e., between the actors or between the materials). However, we can assume that implicit affinities might exist between the actors who used the same materials or between the materials that were used by the same actors.

The same data may also be represented in matrix form (b), which is called an incidence matrix. In an incidence matrix, an arbitrary element $[a]_{ij}$ is unity when an edge exists between nodes i and j, this means a relationship exists between these two nodes. When no edge is recognized for an arbitrary element $[a]_{ij}$, then no relationship exists between nodes i and j, and the element is zero.

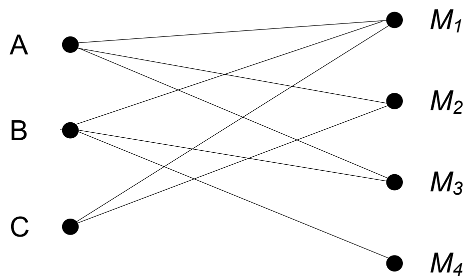

Figure 2. Example of a bipartite graph.

$$\text{incidence matrix} = \begin{array}{c} \\ \text{A} \\ \text{B} \\ \text{C} \end{array} \begin{array}{c} \begin{array}{cccc} M_1 & M_2 & M_3 & M_4 \end{array} \\ \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \end{pmatrix} \end{array} \qquad \text{(b)}$$

In addition, an incidence matrix such as (b) can be divided into two adjacency matrices by means of a transposed matrix. The transpose of matrix (b) is given by matrix (c).

$$\text{transposed matrix} = \begin{array}{c} \\ M_1 \\ M_2 \\ M_3 \\ M_4 \end{array} \begin{array}{c} \begin{array}{ccc} \text{A} & \text{B} & \text{C} \end{array} \\ \begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \end{array} \qquad \text{(c)}$$

If A is a $m \times n$ matrix with elements $[i, j]$, A and its transposed matrix are related as follows:

$$[A]_{ij} = [A^{t}]_{ji} \qquad \text{(d)}$$

To investigate the implicit relationship between the row elements (A, B, and C), the incidence matrix (b) is multiplied by its transposed matrix (c). The result is the adjacency matrix (e):

$$A \times A^t = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix} = \begin{array}{c} \\ A \\ B \\ C \end{array} \begin{array}{c} \begin{array}{ccc} A & B & C \end{array} \\ \begin{pmatrix} 3 & 2 & 2 \\ 2 & 3 & 1 \\ 2 & 1 & 2 \end{pmatrix} \end{array} \quad \text{(e)}$$

The result (e) indicates that:

1. A × A gives that the number of the different materials that A used (i.e., 3),
2. A × B gives that the number of the different materials that both A and B used (i.e., 2),
3. A × C gives that the number of the different materials that both A and C used (i.e., 2),
4. B × B gives that the number of the different materials that B used (i.e., 3),
5. B × C gives that the number of the different materials that both B and C used (i.e., 1),
6. C × C gives that the number of the different materials that C used (i.e., 2).

Similarly, to investigate the relationship between the column elements (M_1, M_2, M_3, and M_4), the transposed matrix (c) is multiplied by the incidence matrix (b). The result is the adjacency matrix (f).

$$A^t \times A = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \end{pmatrix} = \begin{array}{c} \\ M_1 \\ M_2 \\ M_3 \\ M_4 \end{array} \begin{array}{c} \begin{array}{cccc} M_1 & M_2 & M_3 & M_4 \end{array} \\ \begin{pmatrix} 3 & 2 & 2 & 1 \\ 2 & 2 & 1 & 0 \\ 2 & 1 & 2 & 1 \\ 1 & 0 & 1 & 1 \end{pmatrix} \end{array} \quad \text{(f)}$$

The result (f) indicates that:

1. $M_1 \times M_1$ gives the number of actors that used M_1 (i.e., 3),
2. $M_1 \times M_2$ gives the number of actors that used both M_1 and M_2 (i.e., 2),
3. $M_1 \times M_3$ gives the number of actors that used both M_1 and M_3 (i.e., 2),
4. $M_1 \times M_4$ gives the number of actors that used both M_1 and M_4 (i.e., 1),
5. $M_2 \times M_2$ gives the number of actors that used M_2 (i.e., 2),

6. $M_2 \times M_3$ gives the number of actors that used both M_2 and M_3 (i.e., 1),
7. $M_2 \times M_4$ gives the number of actors that used both M_2 and M_4 (i.e., 0),
8. $M_3 \times M_3$ gives the number of actors that used M_3 (i.e., 2),
9. $M_3 \times M_4$ gives the number of actors that used both M_3 and M_4 (i.e., 1),
10. $M_4 \times M_4$ gives the number of actors that used M_4 (i.e., 1).

These concepts and mathematical operations of the bipartite graph and the incidence matrix are some of the essential elements of social-network analysis, and they have been extensively applied in many studies (Christakis & Fowler, 2009; de Nooy, Mrvar, & Batagelj, 2005). In this article, the bipartite graph and the incidence matrix are also used to investigate student learning behavior in a Web-based learning environment.

3. Method

3.1 Participants

A new quantitative research method combining access-log analysis and social-network analysis was tested on sixteen (6 males and 10 females) 2nd-year undergraduate students for one and a half months from the beginning of June to the end of July, 2010. Each student was labeled with an identification number from St01 to St16. One 90-minute in-class lesson was held once a week and eight lessons were conducted during the research period in a CALL classroom. In addition, each student had internet-connected computers at home and several open-computer lounges were available at the university. The university is located in northern Kobe, Japan, in the center of a newly developed residential area. The instructor responsible for the course had over four years of teaching experience at the university level and holds a doctorate in foreign-language teaching. His mother tongue is Japanese, but his English proficiency is high.

The course used in this study was designed for students who plan to apply for an overseas-study program offered by the university. The purpose of the course was to improve student reading scores on the TOEIC® test. To join the course, students were required to satisfy the minimum TOEIC® English-proficiency requirements (i.e., obtain a score of around 400) and to pass an interview test in English. The students who were selected for the course had a relatively low level of English for university students with their TOEIC® scores (M = 423.57, SD = 91.30), but they were highly motivated by their desire to participate in the overseas-study program.

3.2 Instructional Design

The course design was based on the cyclic model of learning (Takeuchi, 2007), whose most distinctive feature is its integration of in-class practices and technologically assisted out-of-class self-learning (Sumi & Takeuchi, 2010). To integrate in- and out-of-class learning, the preparation and reflection phases were connectedly placed before and after the in-class lesson via technologies.

In the preparation phase, learning resources that are related to the lesson are provided with the aid of technology to prepare students for the lesson. During the lesson, the tutor facilitates the students' use of the target language and elicits their participation in classroom activities. In the reflection phase, students are asked to review the lesson by using the electronically provided learning resources. By connecting the preparation, lesson, and reflection, the cyclic model of learning makes it possible to expand the time and space for teaching and learning, thereby creating a learning cycle. Figure 3 schematically shows the framework of the model.

To integrate preparation, lesson, and reflection, *Moodle* (ver. 1.9.10) was used. *Moodle* is a well-known open-source CMS that is widely used for foreign-language education. The students were able to log into *Moodle* and use the learning materials provided wherever they had an internet-connected computer.

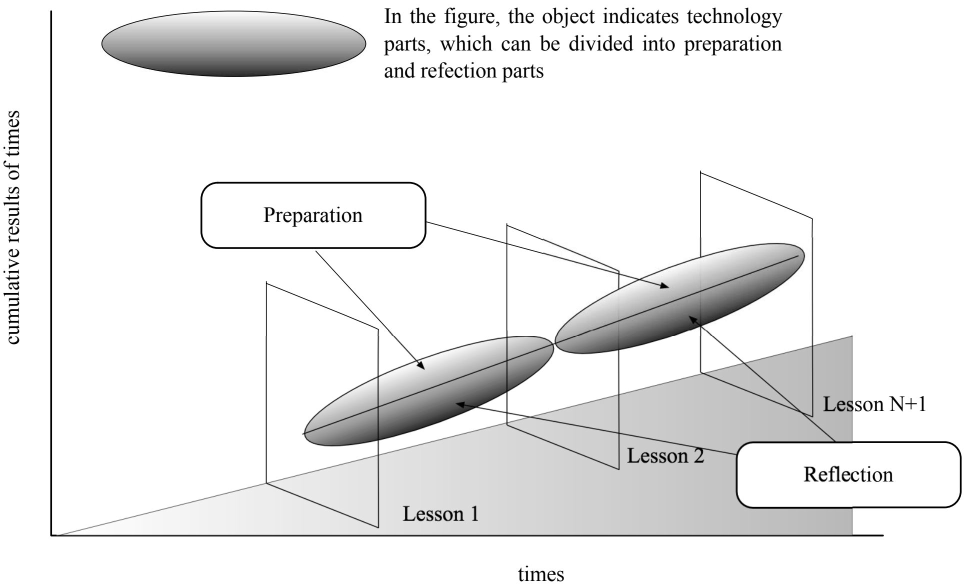

Figure 3. Schematic of framework of the cyclic model of learning. Technology parts play a role of junction areas between lessons. On the technology parts, materials for preparation and reflection are provided.

All learning materials were designed and provided by the tutor, who also directed the classroom lessons. Table 1 gives the list of the materials. The course used 21 different supporting materials; nine for preparation labeled e-01 to e-09, seven for reflection labeled HW-01 to HW-07, and five kinds of self-learning materials labeled test-01 to test-05. All these materials were available for students to use in their free time.

Table 1
List of the Learning Materials

Segments	ID	Name of the material
Preparation		
	e-01	06_Preparation
	e-02	07_Preparation
	e-03	08_Preparation
	e-04	09_Preparation
	e-05	10_Preparation
	e-06	11_Preparation
	e-07	12_Preparation
	e-08	13_Preparation
	e-09	14_Preparation
Reflection		
	HW-01	Review of Unit 5
	HW-02	Review of Unit 6
	HW-03	Review of Unit 7
	HW-04	Review of Unit 8
	HW-05	Review of Unit 9
	HW-06	Review of Unit 10
	HW-07	Review of Unit 11
Self-learning		
	test-01	TOEIC® Listening Part 1
	test-02	TOEIC® Listening Part 2
	test-03	TOEIC® Listening Part 3
	test-04	TOEIC® Grammar Part 5
	test-05	TOEIC® Grammar Part 5

3.3 Data Collection

Google Analytic was used to collect students' personal access-log data. *Google Analytics* is an advanced Web analytics solution that makes it possible to analyze Web traffic data in a variety of ways. It is available for free and easy to use.[3]

It is easy to synchronize *Google Analytics* with the Web-site for which you want to collect visitor access data. One simply adds tracking codes generated by *Google Analytics* to the Web-site, and *Google Analytics* automatically starts collecting data.[4]

However, it is not possible, with this default configuration, to trace personal access-log data of Web visitors or users because *Google Analytics* collects personal information anonymously. To collect personal access-log data and trace visitor behavior on the Web site (i.e., to collect student personal access-log data and trace their learning behavior on *Moodle*), the author developed *JavaScript* and *PHP* programs that were incorporated into the original code. The details of these programs are provided and explained in the online supplemental material.[5] With the help of these programs, *Google Analytics* was fully integrated with *Moodle*, allowing student personal access-log data to be stored on *Google Analytics*. Figure 4 shows a screenshot of a student's personal access-log data acquired during the research period.[6]

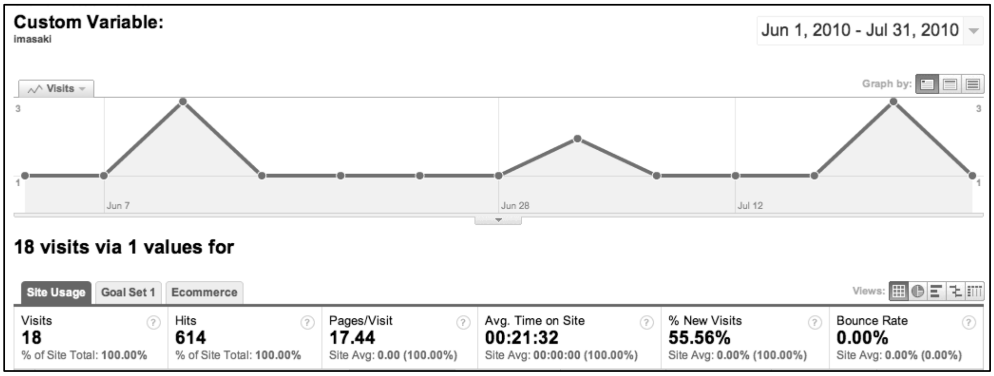

Figure 4. Example of a student's personal access-log data displayed on *Google Analytics*

3.4 Data Analysis

The software packages *R* (ver. 2.11.1) and *Pajek* (ver. 2.01) were used for data analysis.[8] *R* is free software for statistical processing, and *Pajek* is also free software for social-network analysis.

For the analysis, the following data were first extracted from the database: (a) the number of times each student used the learning materials on *Moodle*, and (b) the student online-test scores. Two incidence matrices g_1 and g_2 were formed.

The incidence matrix $[g_1]_{ij}$ consists of

- i: ID number for student i,
- j: ID number of the learning material j,
- $i \times j$: the number of times student i used material j.

The incidence matrix $[g_2]_{ij}$ consists of

i: ID number for student i,

j: ID number of the learning material j,

$i \times j$: the data set for the student online-test scores.

Second, the correlation coefficient between (a) and (b) was investigated, and the total sum of these two data was used as weight for the new compound incidence matrix g. The new compound incidence matrix g was generated by summing g_1 and g_2.

The compound incidence matrix $[g]_{ij}$ consists of

i: ID number for students i,

j: ID number for learning material j,

$i \times j$: the sum of g_1 and g_2.

Third, the compound incidence matrix g was analyzed via *Pajek* to investigate the general network data. In addition, the compound incidence matrix g was visualized, which represents the topology of the student learning behavior in the Web-based learning environment.

Finally, the compound incidence matrix g was divided into two adjacency matrices (see Section 2. Access-Log Analysis and Social-Network Analysis); one to investigate the relationships between the students (st) and the other to investigate the relationships between the materials (m).[9] Cluster analysis and blockmodeling analysis were then conducted on the adjacency matrices st and m. The results of cluster analysis and blockmodeling help us identify the potential relationships and structures between the elements.

4. Results

4.1 Access-Log Data

Table 2 summarizes the personal access-log data obtained with *Google Analytics*. In Table 2, the entries under “Visit” give the total number of sessions initiated by the students during the research period. A single session is initiated when a student logs into *Moodle* and is updated each time the same student visits a different *Moodle* page. This single session terminates when the student logs out of *Moodle* or pauses on a page longer than 30 minutes.[10] The entries under “Page views” give the total number of pages visited by each given student during the research period. The entries under

"Page/Visit" give the average number of pages visited by each given student within a single session. Finally, the entries under "Avg. time on site" give the average time that each given student spent on *Moodle* in a single session. According to Table 2, the number of visits is greater than the number of lessons during the research period, and "Page/Visit" data show that the students visited more pages per visit than was required of them for preparation and reflection.

Table 2
Overview of the Site Usage

ID	Visits	Page views	Pages/Visit	Avg. time on site
ST-01	10.00	83.00	8.30	0:06:36
ST-02	16.00	287.00	17.94	0:15:53
ST-03	11.00	113.00	10.27	0:10:02
ST-04	9.00	122.00	13.56	0:12:47
ST-05	9.00	144.00	16.00	0:12:32
ST-06	17.00	195.00	11.47	0:12:57
ST-07	10.00	106.00	10.60	0:08:13
ST-08	13.00	190.00	14.62	0:10:37
ST-09	11.00	130.00	11.82	0:07:35
ST-10	18.00	314.00	17.44	0:21:32
ST-11	9.00	161.00	17.89	0:14:19
ST-12	20.00	195.00	9.75	0:10:38
ST-13	8.00	128.00	16.00	0:24:06
ST-14	11.00	140.00	12.73	0:21:31
ST-15	11.00	213.00	19.36	0:08:41
ST-16	13.00	254.00	19.54	0:14:53
Total	196.00	2775.00	227.29	3:32:52
M	12.25	173.44	14.21	0:13:18
SD	3.62	66.85	3.64	0:05:15

Figure 5 shows the number of pages visited by each student during the research period. The results clearly show that the student-accesses pattern peaks on the day of lessons and that the number of pages viewed is distinctly different between the students. It is also apparent that they rarely visited the site on non-lesson days.

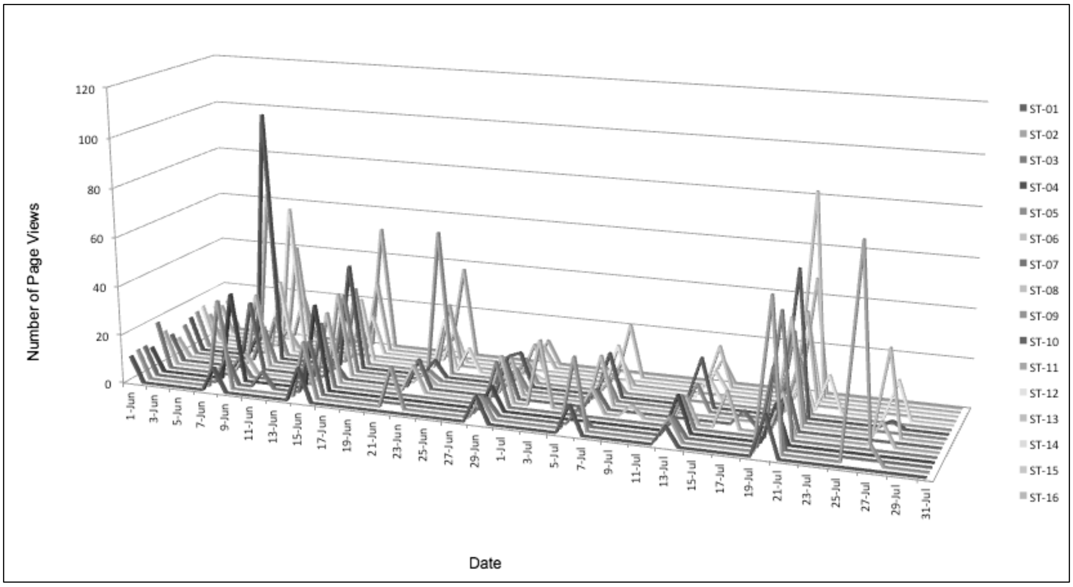

Figure 5. Number of pages visited by each student over the course period.

4.2 Incidence Matrices

Table 3 shows the number of times each student used the learning materials provided on *Moodle* along with the corresponding lessons. The data presented in Table 3 were transformed by *R* into the incidence matrix $[g_1]_{ij}$. The *R* commands are provided in the online supplemental material.[11]

Table 4 shows student online-test scores for the various sections. The data presented in Table 4 were transformed by *R* into the incidence matrix $[g_2]_{ij}$. The *R* commands are also provided in the online supplemental material.[12]

The Spearman rank-correlation was used to identify the correlation between (a) the number of times that the students used the materials, and (b) the student online-test scores of the materials. The results reveal that these variables are strongly correlated (r_s =.93, r_2 = .85, p < .01), so it is appropriate to use the total sum of (a) and (b) as a weight for the new compound incidence matrix g. The incidence matrix g was generated by summing g_1 and g_2. The result is shown in Table 5.[13]

$$[g]_{ij} = [g_1]_{ji} + [g_2]_{ji} \qquad \text{(g)}$$

Table 3

Number of Times Students Accessed the Materials

ID	e-01	e-02	e-03	e-04	e-05	e-06	e-07	e-08	e-09	HW-01	HW-02	HW-03	HW-04	HW-05	HW-06	HW-07	test-01	test-02	test-03	test-04	test-05
ST-01	1	0	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1
ST-02	1	0	1	0	1	1	1	3	1	2	4	3	4	2	2	2	0	0	0	0	0
ST-03	1	0	1	0	0	1	1	1	1	0	0	0	0	0	0	0	1	0	0	1	0
ST-04	1	0	1	0	0	1	0	0	1	0	1	3	1	0	0	1	0	0	0	0	2
ST-05	1	1	1	1	2	2	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
ST-06	1	0	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
ST-07	1	1	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	4
ST-08	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	0	0
ST-09	1	0	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0
ST-10	1	4	1	2	1	1	2	1	1	1	3	3	1	0	0	0	0	2	1	2	1
ST-11	1	0	1	0	0	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0
ST-12	1	2	1	0	0	0	1	1	1	1	1	1	1	0	0	0	2	1	1	1	0
ST-13	1	0	0	0	0	1	1	0	1	1	2	0	0	1	0	1	1	0	1	0	1
ST-14	1	0	1	0	1	1	1	1	1	1	3	2	2	0	0	0	1	0	0	0	0
ST-15	1	0	1	0	1	1	2	1	1	0	2	0	0	0	0	0	1	0	0	0	0
ST-16	1	1	1	1	1	1	1	1	1	2	1	1	0	1	0	1	0	0	0	0	0

Table 4
Student Online-Test Score

ID	e-01	e-02	e-03	e-04	e-05	e-06	e-07	e-08	e-09	HW-01	HW-02	HW-03	HW-04	HW-05	HW-06	HW-07	test-01	test-02	test-03	test-04	test-05
ST-01	5.00	0.00	8.61	0.00	0.00	5.64	2.38	5.64	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00	5.33
ST-02	5.00	0.00	10.00	0.00	6.79	7.45	6.67	10.00	4.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	0.00	0.00	0.00	0.00	0.00
ST-03	4.00	0.00	4.17	0.00	0.00	5.82	0.95	3.45	7.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.45	0.00	0.00	5.00	0.00
ST-04	8.00	0.00	5.83	0.00	0.00	6.18	0.00	0.00	7.33	0.00	2.73	6.36	4.23	0.00	0.00	1.76	0.00	0.00	0.00	0.00	6.33
ST-05	3.00	0.00	7.78	0.00	8.93	6.00	0.00	5.64	7.33	4.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ST-06	6.00	0.00	5.83	0.00	0.00	6.73	7.62	6.73	5.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ST-07	7.00	0.00	9.17	0.00	0.00	6.00	3.33	0.00	7.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.67
ST-08	5.00	0.00	8.06	0.00	3.21	7.82	3.81	4.73	10.00	5.45	3.64	4.55	3.46	0.00	0.00	0.00	5.45	5.00	0.00	0.00	0.00
ST-09	8.00	0.00	10.00	0.00	0.00	6.36	10.00	4.73	2.00	6.36	3.64	3.64	5.77	2.35	0.00	0.00	0.00	0.00	0.00	5.00	0.00
ST-10	5.00	0.00	10.00	0.00	3.57	6.73	10.00	3.45	7.33	5.45	7.27	6.36	3.85	0.00	0.00	0.00	0.00	8.00	5.00	7.00	5.67
ST-11	5.00	0.00	10.00	0.00	0.00	6.73	4.29	2.18	3.33	4.55	4.55	0.00	0.00	0.00	0.00	0.00	2.73	0.00	0.00	0.00	0.00
ST-12	5.00	0.00	8.61	0.00	0.00	0.00	2.38	4.91	3.33	5.45	3.64	4.55	6.92	0.00	0.00	0.00	7.27	6.00	8.33	5.00	0.00
ST-13	7.00	0.00	0.00	0.00	0.00	6.91	8.10	0.00	6.67	5.45	7.27	0.00	0.00	2.35	0.00	3.53	0.91	0.00	3.33	0.00	6.00
ST-14	10.00	0.00	10.00	0.00	7.86	8.18	6.19	7.64	7.33	4.55	10.00	8.18	6.92	0.00	0.00	0.00	9.09	0.00	0.00	0.00	0.00
ST-15	6.00	0.00	6.67	0.00	6.43	8.00	10.00	7.64	6.67	0.00	6.36	0.00	0.00	0.00	0.00	0.00	6.36	0.00	0.00	0.00	0.00
ST-16	10.00	0.00	6.11	0.00	7.50	8.00	8.10	6.36	6.67	10.00	8.18	6.36	0.00	5.29	0.00	5.88	0.00	0.00	0.00	0.00	0.00

Table 5
Compound Incidence Matrix

ID	e-01	e-02	e-03	e-04	e-05	e-06	e-07	e-08	e-09	HW-01	HW-02	HW-03	HW-04	HW-05	HW-06	HW-07	test-01	test-02	test-03	test-04	test-05
ST-01	6.00	0.00	9.61	0.00	0.00	6.64	3.38	6.64	5.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.00	6.33
ST-02	6.00	0.00	11.00	0.00	7.79	8.45	7.67	13.00	5.00	12.00	14.00	13.00	14.00	12.00	12.00	12.00	0.00	0.00	0.00	0.00	0.00
ST-03	5.00	0.00	5.17	0.00	0.00	6.82	1.95	4.45	8.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.45	0.00	0.00	6.00	0.00
ST-04	9.00	0.00	6.83	0.00	0.00	7.18	0.00	0.00	8.33	0.00	3.73	9.36	5.23	0.00	0.00	2.76	0.00	0.00	0.00	0.00	8.33
ST-05	4.00	1.00	8.78	1.00	10.93	8.00	0.00	6.64	8.33	5.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ST-06	7.00	0.00	6.83	0.00	0.00	7.73	8.62	7.73	6.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ST-07	8.00	1.00	10.17	0.00	0.00	7.00	4.33	0.00	8.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.67
ST-08	6.00	1.00	9.06	1.00	4.21	8.82	4.81	5.73	11.00	6.45	4.64	5.55	4.46	0.00	0.00	0.00	6.45	6.00	0.00	0.00	0.00
ST-09	9.00	0.00	11.00	0.00	0.00	7.36	11.00	5.73	3.00	7.36	4.64	4.64	6.77	3.35	0.00	0.00	0.00	0.00	0.00	6.00	0.00
ST-10	6.00	4.00	11.00	2.00	4.57	7.73	12.00	4.45	8.33	6.45	10.27	9.36	4.85	0.00	0.00	0.00	0.00	10.00	6.00	9.00	6.67
ST-11	6.00	0.00	11.00	0.00	0.00	7.73	5.29	3.18	4.33	5.55	5.55	0.00	0.00	0.00	0.00	0.00	3.73	0.00	0.00	0.00	0.00
ST-12	6.00	2.00	9.61	0.00	0.00	0.00	3.38	5.91	4.33	6.45	4.64	5.55	7.92	0.00	0.00	0.00	9.27	7.00	9.33	6.00	0.00
ST-13	8.00	0.00	0.00	0.00	0.00	7.91	9.10	0.00	7.67	6.45	9.27	0.00	0.00	3.35	0.00	4.53	1.91	0.00	4.33	0.00	7.00
ST-14	11.00	0.00	11.00	0.00	8.86	9.18	7.19	8.64	8.33	5.55	13.00	10.18	8.92	0.00	0.00	0.00	10.09	0.00	0.00	0.00	0.00
ST-15	7.00	0.00	7.67	0.00	7.43	9.00	12.00	8.64	7.67	0.00	8.36	0.00	0.00	0.00	0.00	0.00	7.36	0.00	0.00	0.00	0.00
ST-16	11.00	1.00	7.11	1.00	8.5	9.00	9.1	7.36	7.67	12.00	9.18	7.36	0.00	6.29	0.00	6.88	0.00	0.00	0.00	0.00	0.00

4.3 Social-Network Analysis

The *Pajek* software package was used to investigate the structure of the compound incidence matrix *g*. The results indicated:

- number of lines = 174,
- density = 0.25,
- average degree = 9.40.

In social-network analysis, the network density, which ranges from 0 to 1, indicates the degree of cohesiveness between the nodes and edges in a network. The average degree indicates the average number of edges per node. The results indicate that the network of the Web-based learning environment has low cohesiveness.

Table 6 shows the input degree number and closeness centrality for each node. The input degree number indicates the total number of edges for each node, and the closeness centrality represents the distance from the center of the network. In other words, if one node has more edges than others nodes, the possibility increases for the given node to approach the center of the network and thereby to play an important role in the network.

Table 7 shows the data obtained from Table 6 for the 16 students. The data were sorted by descending input-degree-number order. The results allow us to predict that the top five students in terms of input degree number (i.e., ST-10, ST-08, ST-02, ST-12, and ST-16) will be positioned in the pericentral area of the network. To identify the position of these nodes, a sociogram was drawn following the Kamada and Kawai (1989) algorism (Figure 6).[14] The sociogram also presents the topology of the network and helps in understanding the structure of the Web-based learning environment. The results displayed in Figure 6 show that the students ST-10, ST-08, ST-12, and ST-16 indeed figure in the center of the sociogram, as predicted by the results shown in Table 7. Student ST-02, however, appears at the periphery of the sociogram because of the strong tie with HW-06. Student ST-02 was the only student to use HW-06 two times and the weight between ST-02 and HW-06 is 12 (see Table 5), which results in ST-02 being strongly repelled from the center and the edges connected to ST-02 being stretched. In addition, ST-06, who did not proactively use the learning materials, appears at the periphery of the sociogram and is connected by only a few weak edges.

Table 6

Input Degree Number and Closeness Centrality

ID	Input degree number	Closeness centrality
e-01	16	0.64
e-02	6	0.46
e-03	15	0.62
e-04	4	0.44
e-05	7	0.49
e-06	15	0.62
e-07	14	0.60
e-08	13	0.58
e-09	16	0.64
HW-01	10	0.53
HW-02	11	0.55
HW-03	8	0.50
HW-04	7	0.49
HW-05	4	0.44
HW-06	1	0.36
HW-07	4	0.43
test-01	7	0.47
test-02	3	0.41
test-03	3	0.43
test-04	5	0.44
test-05	5	0.45
ST-01	8	0.47
ST-02	14	0.55
ST-03	8	0.47
ST-04	9	0.48
ST-05	9	0.48
ST-06	6	0.44
ST-07	7	0.46
ST-08	15	0.57
ST-09	12	0.52
ST-10	17	0.61
ST-11	9	0.48
ST-12	14	0.55
ST-13	11	0.51
ST-14	12	0.52
ST-15	9	0.48
ST-16	14	0.55

Table 7

Input Degree Number and Closeness Centrality of Students

ID	Input degree number	Closeness centrality
ST-10	17	0.61
ST-08	15	0.57
ST-02	14	0.55
ST-12	14	0.55
ST-16	14	0.55
ST-09	12	0.52
ST-14	12	0.52
ST-13	11	0.51
ST-04	9	0.48
ST-05	9	0.48
ST-15	9	0.48
ST-11	9	0.48
ST-01	8	0.47
ST-03	8	0.47
ST-07	7	0.46
ST-06	6	0.44

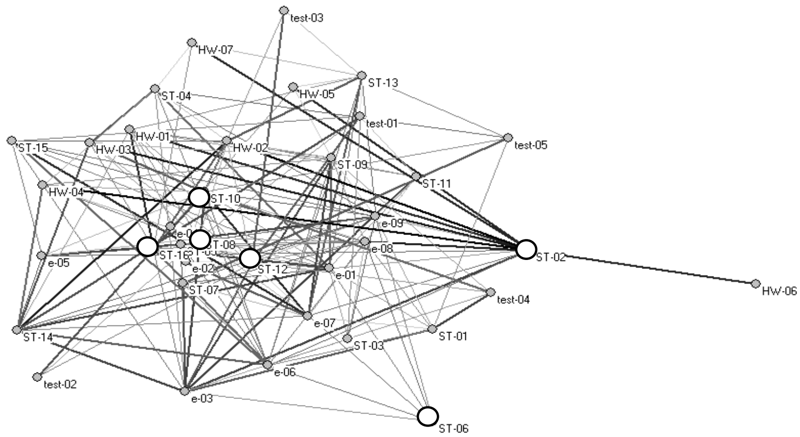

Figure 6. The sociogram represents the structure of the network. The white circles indicate the positions of ST-10, ST-08, ST-02, ST-12, ST-16, and ST-06. The line weights represent the weight of each edge (i.e., two nodes connected by a thick dark line are weighted more than nodes connected by thin light lines.)

4.4 Adjacency Matrices for Students and Materials

Table 8 presents the adjacency matrix *st* for the students, and Table 9 presents the adjacency matrix *m* for the materials provided on *Moodle*. These adjacency matrices were generated from the compound incidence matrix *g* (see Section 3.4 Data Analysis).

To investigate the relationships and structure between elements, cluster analysis and blockmodeling analysis were conducted by using *R* on *st* and *m* respectively (see the online supplemental material[15]). The Euclidean distance was used as a measure of structural equivalence (Wasserman & Faust, 1994, p. 367), and the complete linkage method was used for clustering. Figure 7 gives the result of cluster analysis of *st*. The top five students in Table 7 are also clustered in a group in Figure 7. Figure 8 presents the result of blockmodeling analysis of *st*. Students who proactively used materials appear in darker shades in the upper-left 7 × 7 square of Figure 8. The shading of the squares gradually lightens from the upper-left to the lower-right corner, along with the degree of participation of the students in the Web-based learning environment.

Figures 9 and 10 show the result of cluster analysis and blockmodeling analysis of *m*, respectively. These results show that the materials e-01, e-03, e-06, e-07, e-08 and e-09 were used more frequently for preparation than the other materials. In addition, the results indicate that the materials for test-01 to test-05, which were provided for self-learning, were less used than the other materials (thus they appear in the lower-right corner in Figure 10).

Table 8

Adjacency Matrix for Students

ID	ST-01	ST-02	ST-03	ST-04	ST-05	ST-06	ST-07	ST-08	ST-09	ST-10	ST-11	ST-12	ST-13	ST-14	ST-15	ST-16
ST-01	8	6	7	5	5	6	6	6	7	8	6	6	5	6	6	6
ST-02	6	14	6	8	7	6	5	11	11	11	8	9	8	11	8	12
ST-03	7	6	8	4	5	6	5	7	7	7	7	7	5	7	7	6
ST-04	5	8	4	9	4	4	5	7	7	8	5	6	6	7	5	7
ST-05	5	7	5	4	9	5	5	9	6	9	6	6	4	7	6	9
ST-06	6	6	6	4	5	6	5	6	6	6	6	5	4	6	6	6
ST-07	6	5	5	5	5	5	7	6	5	7	5	5	5	5	5	6
ST-08	6	11	7	7	9	6	6	15	10	14	9	12	7	12	9	12
ST-09	7	11	7	7	6	6	5	10	12	11	8	10	7	10	7	10
ST-10	8	11	7	8	9	6	7	14	11	17	8	13	8	11	8	12
ST-11	6	8	7	5	6	6	5	9	8	8	9	8	7	9	8	8
ST-12	6	9	7	6	6	5	5	12	10	13	8	14	7	10	7	9
ST-13	5	8	5	6	4	4	5	7	7	8	7	7	11	7	6	8
ST-14	6	11	7	7	7	6	5	12	10	11	9	10	7	12	9	10
ST-15	6	8	7	5	6	6	5	9	7	8	8	7	6	9	9	8
ST-16	6	12	6	7	9	6	6	12	10	12	8	9	8	10	8	14

Table 9

Adjacency Matrix for Materials

ID	e-01	e-02	e-03	e-04	e-05	e-06	e-07	e-08	e-09	HW-01	HW-02	HW-03	HW-04	HW-05	HW-06	HW-07	test-01	test-02	test-03	test-04	test-05
e-01	16	6	15	4	7	15	14	13	16	10	11	8	7	4	1	4	7	3	3	5	5
e-02	6	6	6	4	4	5	5	5	6	5	4	4	3	1	0	1	2	3	2	2	2
e-03	15	6	15	4	7	14	13	13	15	9	10	8	7	3	1	3	6	3	2	5	4
e-04	4	4	4	4	4	4	3	4	4	4	3	3	2	1	0	1	1	2	1	1	1
e-05	7	4	7	4	7	7	6	7	7	6	6	5	4	2	1	2	3	2	1	1	1
e-06	15	5	14	4	7	15	13	12	15	9	10	7	6	4	1	4	6	2	2	4	5
e-07	14	5	13	3	6	13	14	12	14	9	10	7	6	4	1	3	7	3	3	5	4
e-08	13	5	13	4	7	12	12	13	13	9	9	7	6	3	1	2	6	3	2	5	2
e-09	16	6	15	4	7	15	14	13	16	10	11	8	7	4	1	4	7	3	3	5	5
HW-01	10	5	9	4	6	9	9	9	10	10	9	7	6	4	1	3	5	3	3	3	2
HW-02	11	4	10	3	6	10	10	9	11	9	11	8	7	4	1	4	6	3	3	3	3
HW-03	8	4	8	3	5	7	7	7	8	7	8	8	7	3	1	3	3	3	2	3	2
HW-04	7	3	7	2	4	6	6	6	7	6	7	7	7	2	1	2	3	3	2	3	2
HW-05	4	1	3	1	2	4	4	3	4	4	4	3	2	4	1	3	1	0	1	1	1
HW-06	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
HW-07	4	1	3	1	2	4	3	2	4	3	4	3	2	3	1	4	1	0	1	0	2
test-01	7	2	6	1	3	6	7	6	7	5	6	3	3	1	0	1	7	2	2	2	1
test-02	3	3	3	2	2	2	3	3	3	3	3	3	3	0	0	0	2	3	2	2	1
test-03	3	2	2	1	1	2	3	2	3	3	3	2	2	1	0	1	2	2	3	2	2
test-04	5	2	5	1	1	4	5	5	5	3	3	3	3	1	0	0	2	2	2	5	2
test-05	5	2	4	1	1	5	4	2	5	2	3	2	2	1	0	2	1	1	2	2	5

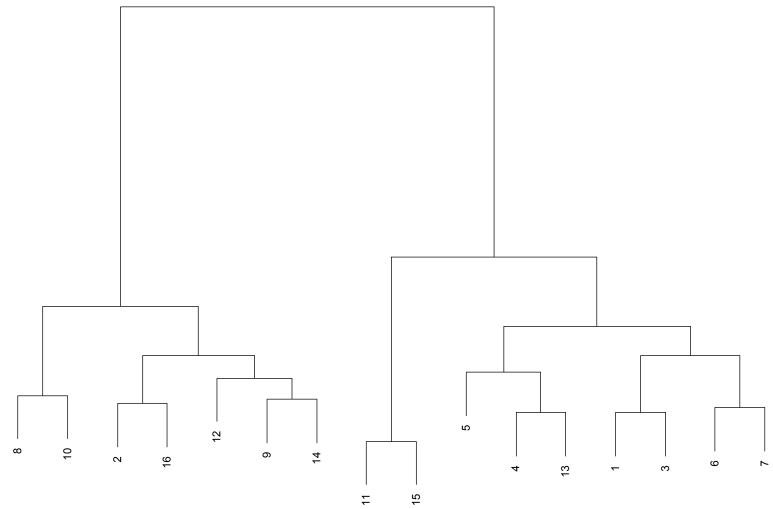

Figure 7. Result of cluster analysis of matrix *st*. The students who proactively used the web-based materials are clustered on the left-hand hierarchical bars, and those who did not are clustered on the right-hand hierarchical bars. 1 = ST-01; 2 = ST-02; 3 = ST-03; 4 = ST-04; 5 = ST-05; 6 = ST-06; 7 = ST-07; 8 = ST-08; 9 = ST-09; 10 = ST-10; 11 = ST-11; 12 = ST-12; 13 = ST-13; 14 = ST-14; 15 = ST-15; 16 = ST-16.

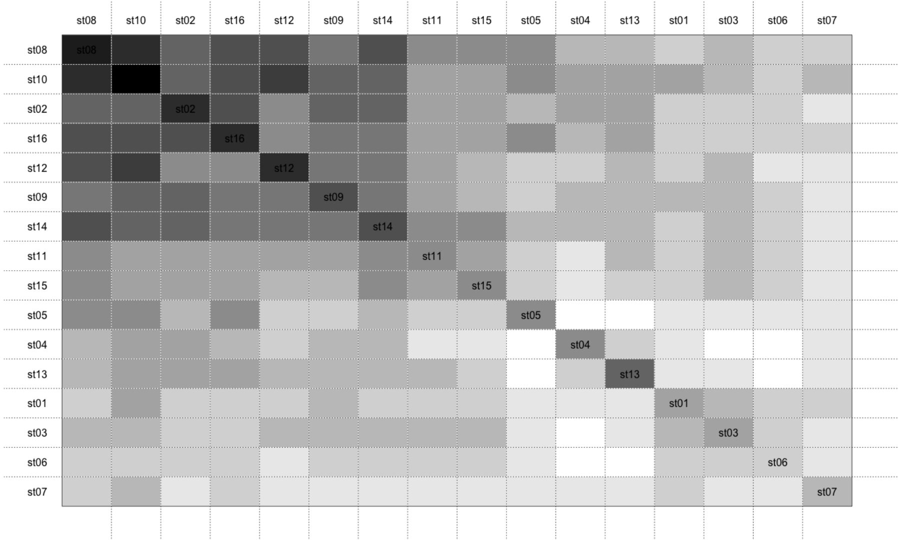

Figure 8. Result of blockmodeling analysis of matrix *st*. The students are clustered along with the edge weights. The students who used the web-based materials appear in the upper-left corner in dark-shaded squares. The shading indicated the students' degree of participation in the network.

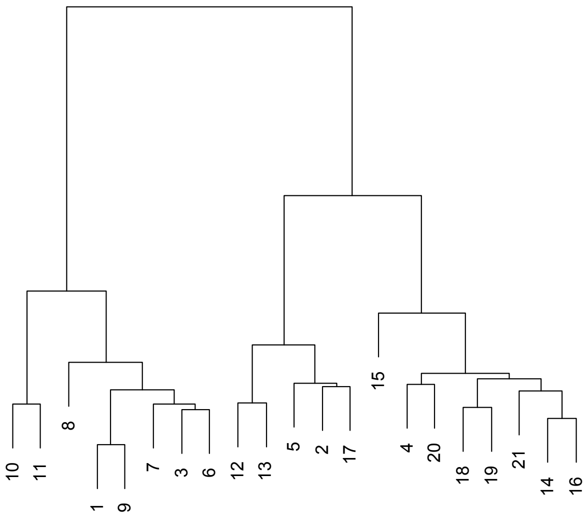

Figure 9. Result of cluster analysis of matrix *m*. 1 = e-01; 2 = e-02; 3 = e-03; 4 = e-04; 5 = e-05; 6 = e-06; 7 = e-07; 8 = e-08; 9 = e-09; 10 = HW-01; 11 = HW-02; 12 = HW-03; 13 = HW-04; 14 = HW-05; 15 = HW-06; 16 = HW-07; 17 = test-01; 18 = test-02; 19 = test-03; 20 = test03; 21 = test-04.

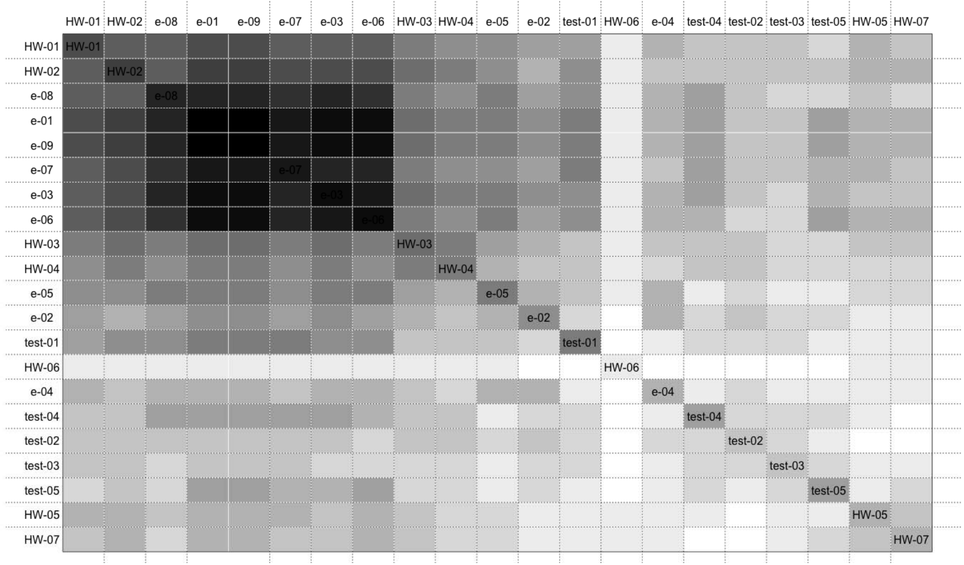

Figure 10. Result of blockmodeling analysis of *m*. The materials are clustered and shaded according to their frequency of usage. The more frequently used materials appear in dark shades in the upper-left corner.

5. Discussion

This study presents a new quantitative research method to investigate student English-learning behavior in a Web-based learning environment. The combination of access-log analysis and social-network analysis was tested on 16 undergraduate students over a period of one and a half months.

First, to obtain an overall perspective on individual learning behavior in a Web-based learning environment, the student personal access-log data were collected and analyzed. The results show that the students accessed the Web-based material on lesson days much more than on non-lesson days. In addition, the students visited more pages than they were asked to visit for preparation and reflection. This behavior may be due to their visiting course-related Web-based supplements that the author provided on *Moodle*.

Second, the compound incidence matrix *g* was generated to investigate in detail the overall network structure and the individual learning behavior on the Web; that is, what students were using for learning and how students were learning. A social-network analysis was conducted on *g* and the sociogram was drawn with *Pajek*. The result shows the general network features of the Web-based learning environment, and each student's position and implicit relationships with other students in the network are clearly revealed.

Finally, cluster analysis and blockmodeling analysis were conducted on the adjacency matrices *st* and *m*. The frequency of use of the Web-based materials determines the student results in *st*; in other words, their degree of participation in the learning community. The students who regularly used Web-based materials share densely connected edges and are positioned close to the center of the network. These students also played the role of the network *hub*. Conversely, the students who used the materials less frequently (i.e., those who did not fully participate in the learning community), were weakly connected with their colleagues. The adjacency matrix *m* reveals that the materials used were determined by their frequency of use. The materials most often used along with the lesson for preparation and reflection are the most densely connected and the closest to the center of the network where they connect with the hub-students. The results of this analysis of *st* and *m* are well represented in the structure of the sociogram.

The structures and relationships revealed by the adjacency matrix *m* are worthy of attention. The materials for preparation (e-01, e-03, e-06, e-07, e-08, and e-09) and reflection (HW-01, HW-02, HW-03, and HW-04) were used more than the other materials and so are positioned near the center of the sociogram with densely connected edges. This result implies that the lessons performed the mainstay of the learning cycle and the materials were used corresponding to the lessons for preparation and reflection; that is, the lessons provided the on-going context that connected the various types of materials in the network and allowed the students to navigate through the Web-based materials. In addition, the materials for preparation were used more than those for reflection, although this may be because quizzes were conducted at the beginning of each lesson to check the results of the preparation. Accordingly, students had more incentive to use the materials for preparation. Conversely, the materials for self-learning were rarely used by students, which may be because they were provided regardless of the lesson context and the students were asked to use them during their free time. These results suggest that the lesson context should be considered in designing and providing learning materials and a Web-based learning environment to encourage students to participate in the learning community and to allow them to study autonomously on the Web.

These results and the accompanying discussion demonstrate the answers to the research questions in this study.

1. *Is the use of the combination of access-log analysis and social-network analysis effective in investigating student learning behavior in a Web-based learning environment?*

With the help of access-log analysis and social-network analysis, it has come to be possible to understand the behavior of students learning via the Web and to visualize the Web-based learning environment. In addition, the sociogram helps to instinctively understand the structure of the Web-based learning environment and student Web-based learning behavior. Therefore, it can be said that the proposed quantitative research method, which combines access-log analysis and social-network analysis, is effective in investigation student learning behavior in a Web-based learning environment.

2. *What kinds of student learning behavior can be identified with the use of the combination of access-log analysis and social-network analysis?*

As the results of the use of the combination of access-log analysis and social-network analysis, students learning behavior were identified corresponding to the degree of their use of learning materials provided on the Web. In addition, students who proactively participated in lessons and the Web-based learning community were clustered in the same group and shared the central position of the network. They played the role as *hubs* of the network and functioned as *anchors* to maintain the network cohesiveness.

6. Conclusion

Before concluding the study, a few limitations should be considered. The number of students who participated was rather small. Comparative studies are needed in several different environments and with large numbers of participants. Qualitative data-analysis methods should be also considered. The data collected in the present study were the frequency with which students used the materials and their online-test scores. To investigate student learning behavior in more detail, qualitative data such as classroom observation and interviews should be considered, and research should shift the frame of reference from "learning behavior *in* the Web-base learning environment" to "learning behavior *within* the Web-based learning environment." In this way, it would be possible to explain *the quality of the edge*s that connect each node in a network to "understand effectiveness in terms of the specifics of what people do with computers, how they do it, what it means to them" (Kern, 2006, p. 189).

To bring forward this research method and think future possibilities, some educational implications are mentioned. The results of the use of the combination of access-log analysis and social-network analysis provide informative resources to reflect practices. For example, by identifying *hub* students in the middle of the school term, who share the central position in lessons, and mixing them with less active students in lessons, we can design appropriate students' peer group. Also, the results allow us to identify students who need more learning supports than others and help us give them special care considering their learning characteristics. In addition, the results given by the proposed research method are useful for identifying learning materials that should be modified. For example, in this study, the clustered group of learning materials, which includes HW-06, needs to be reconsidered. In this way, the use of the combination of access-log analysis and social-network analysis is not only effective as a quantitative research method, but also useful as a means of improving practices.

Despite the limitations, the proposed research method was successfully implemented and tested. The author insists that this research method represents a practical way to quantitatively investigate students learning behavior in a Web-based environment. In addition, the analysis gives insights into Web-based practices for CALL studies and indicates directions to take to promote the integration of Web-based technologies into CALL practices.

Notes

1. See Garrett (2009) for more details.
2. See Levy (2009) for more details.
3. *Google Analytics*: http://www.google.com/intl/en_uk/analytics/
4. According to the *Google Analytics Help*, it says that: “copy and paste the code segment into the bottom of your content, immediately before the </body> tag of each page you are planning to track.” However, this is not correct. Since 1 May, 2010, *Google* has changed the tracking system from synchronous snippet to asynchronous snippet, so that the code must be placed just *before* the closing </head> tag on each page.
5. Provided at http://lang-tech.net/data/tracking_code.html
6. Information given by the author is available in Japanese on the Moodle Forum (http://moodle.org/mod/forum/discuss.php?d=150538), also in English (http://moodle.org/mod/forum/discuss.php?d=150541&parent=661805).
7. See more detail about *Google Analytics* private policy at http://www.google.com/intl/en/analytics/privacyoverview.html
8. *R* is downloadable at http://www.r-project.org/
   Pajek is downloadable at http://pajek.imfm.si/doku.php
9. The adjacency matrices of st and m are calculated as below:
   $$[st]_{ij} = [g]_{ij} \times {}^{t}[g]_{ij} \qquad [m]_{ij} = {}^{t}[g]_{ij} \times [g]_{ij}$$
10. More detail is available at http://code.google.com/intl/ja/apis/analytics/docs/concepts/gaConceptsCookies.html
11. Provided at http://lang-tech.net/data/R_commands_g1.html
12. Provided at http://lang-tech.net/data/R_commands_g2.html
13. *R* command for compounding matrices is g <- g1 + g2
14. Kamada and Kawai (1989) algorism is optimized to find a set of coordinates in which the distance between two nodes balances in proportion.
15. Provided at http://lang-tech.net/data/Cluster_Blockmodeling.html

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