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APPLIED CLUSTERING ANALYSIS FOR GROUPING BEHAVIOUR OF E-LEARNING USAGE BASED ON MEANINGFUL LEARNING CHARACTERISTICS

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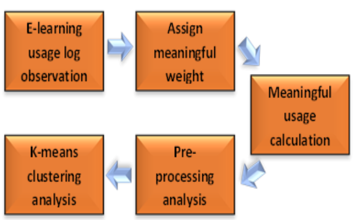
Graphical abstract



Abstract

One of the critical success factors of e-learning is positive interest of students towards e-learning. The majority of activities of current e-learning usage are viewing and downloading. These activities are not meaningful with regard to enhancing learning quality. Due to that, the aim of this paper is to analyze students' usage based on meaningful learning characteristics by clustering students' activities and actions during online learning. We first define meaningful learning characteristics (as those which are active, authentic, cooperative, collaborative, and intentional) and associate these with e-learning activities and actions. Then, we analyze the students' e-learning usage and define the cluster of student's meaningful characteristics by using the K-Means cluster method. A case study has been conducted based on the e-learning log files of 37 students on Computational Intelligence Course at the Software Engineering Department, Universiti Teknologi Malaysia. The result of this clustering enables us to determine the students with high ratings on these meaningful activities and actions during online learning. We found out that students with high hits on add, update, and edit are included in the high cluster group. On the contrary, students with high hits on the view actions for all e-learning activities are included in the low cluster group. This result may assist instructors while preparing the strategy of computer usage for education, in terms of providing a greater variety of learning activities, which is applicable for any courses.

Keywords: E-learning activities and actions, meaningful learning characteristics, k-means clustering

Abstrak

Salah satu faktor kejayaan yang kritikal bagi e-pembelajaran ialah minat positif pelajar terhadap e-pembelajaran. Pada masa kini, majority aktiviti penggunaan e-pembelajaran adalah melihat dan memuat turun. Aktiviti-aktiviti ini tidaklah bermakna berkenaan untuk meningkatkan kualiti pembelajaran. Oleh karena itu, tujuan paper ini ialah untuk menganalisis pengelompokan perilaku pengunaan aktiviti dan tindakan daripada pelajar semasa melakukan pembelajaran dalam talian berdasarkan ciri-ciri pembelajaran bermakna. Pertama kali ialah menentikan ciri-ciri pembelajaran bermakna (aktif, autentik, kooperatif, kolaboratif, dan intentional) dan mengaitkannya dengan aktiviti dan tindakan dalam e-pembelajaran. Kemudian melakukan analisis penggunaan e-pembelajaran dan menentukan kelompok kluster pembelajaran bermakna dengan menggunakan kaedah pengelompokan K-Means. Satu kajian kes telah dijalankan berdasarkan fail log e-pembelajaran dari 37 pelajar pada kursus Kecerdasan Pengkomputeran di Jabaran Kejuruteraan Perisian, Universiti Teknologi Malaysia. Hasil pengelompokan ini membolehkan kita untuk menentukan pelajar dengan penilaian yang tinggi pada aktivitas dan tindakan yang bermakna selama pembelajaran dalam talian. Kami mendapati bahawa pelajar yang mempunyai hits yang tinggi pada aktiviti: tambah, update dan sunting termasuk dalam kumpulan kelompok pembelajaran bermakna tinggi. Sebaliknya, meskipun pelajar memiliki hits yang lebih tinggi dalam tindakan melihat semua aktiviti termasuk dalam kelompok pembelajaran bermakna rendah. Keputusan ini boleh membantu pengajar manakala menyediakan strategi penggunaan komputer untuk pendidikan, dari segi menyediakan lebih banyak pelbagai aktiviti e-pembelajaran yang boleh digunakan untuk mana-mana kursus.

Kata kunci: Aktiviti dan tindakan e-pembelajaran, ciri pembelajaran bermakna, kaedah pengelompokan k-means

1.0 INTRODUCTION

The traditional context of learning is experiencing a radical change. Teaching and learning are no longer limited to traditional classrooms [1]. E-learning refers to the use of electronic devices for learning, including the delivery of content via electronic media such as internet, audio, and so on. With the continuous growth of e-learning as a learning medium, the evaluation of e-learning effectiveness is more and more questioned. Measuring the effectiveness of e-learning is therefore important but it is difficult due to the wide range of components of e-learning. E-learning environments also involve several factors such as students, instructors, content, technology and infrastructure.

One of the critical success factors of e-learning is the engagement by the students [17]. Inspired by that, we suggest that students play the main role within the success of e-learning. With this scenario, instructors should offer various learning methods or learning content that motivate students to participate and interact with one another in online learning environments. In addition, instructors should be able to understand students' behavior during online learning. This is to ensure that students achieve meaningful learning. When students participate in the e-learning system, it will different when they are in the conventional classroom. In the conventional classroom, instructor could observe their behavior include their verb and acts. For the negative results, instructor could encourage the students to be more participating in the class activities such as discussion or group works. In the e-learning environment, students' behavior can be seen in the file called as a log file. This log file stores huge information about activities and actions history performed by students. Some research has been done to analyze students' behavior in e-learning, such as the students' interaction with their instructors or among themselves [2, 3], and students satisfaction [4]. Meanwhile, Arbaugh and Fich studied the importance of participant interaction in online environments [5]. However, most of the existing research has used conventional statistical methods that lack in depth analysis. The investigation continues with data mining approach to evaluate the existence of e-learning. Data mining "is a process that uses statistical, mathematical, artificial and machine learning techniques to extract and identify useful information and subsequent knowledge from large databases" as mentioned by Batware [6]. Following this approach, some scholars have been conducted an investigation and demonstrated the use of data mining technique for e-learning domain. Research by Jui-Long Hung and Ke Zhang has been carried out to grouping students based on their data shared [7], another work in grouping students behavior from their learning patterns was well implemented [8]. Identification students whose require more intention from instructor in a large online class was done by Minaei-Bidgoli *et al.,* [9]. However, the results are unable to show the analysis regarding the students' cognitive behaviour in their online course. Due to that, it is necessary to engage learning pedagogy to do evaluation for e-learning usage, to bring the result to fit to the problem domain. Therefore, this paper proposes a clustering method to examine the students' e-learning usage based on meaningful learning characteristics. The aim of this paper is to cluster students into different groups of meaningful e-learning usage so that by this analysis students and instructors are able to determine whether meaningful online learning has been achieved successfully.

This paper is organized as follows. Section 2 introduces the rationale for classifying meaningful learning characteristics with regard to the e-learning activities and actions. Section 3 presents the methodology for the clustering of e-learning usage. Section 4 describes the findings, while Section 5 covers the discussion and finally Section 6 describes the conclusions and future work.

2.0 E-LEARNING USAGE BASED ON MEANINGFUL LEARNING CHARACTERISTICS

Meaningful learning has been defined for conventional learning in the classroom. Yet, by the inclusion of learning environments which are not limited in the classroom, meaningful learning is helpful to reveal learning personalization [10-12]. Meaningful learning happens when complex ideas and information are merged with students' own experiences and prior knowledge to form personal and unique understandings [13]. Based on the concept of meaningful learning, the instructors should be able to develop the cognitive potential of students through appropriate learning activities. Many researchers have identified meaningful learningcharacteristics as being those which are active, constructive, authentic, and cooperative [14]. Later research extended these characteristics, to include guided-emotionally [15], integrated [16], and intentional [17]. These proposed meaningful learning characteristics are used as benchmarks for analysis of e-learning effectiveness [18]. In this paper, we use five meaningful learning characteristics as suggested by Howland *et al*., namely active, constructive, intentional, authentic, and cooperative [19]. The definitions of the characteristics in the student's perspective are as follows:

(1) *Active*, when students engage in learning by doing. They actively participate in the learning process by interacting with peers and instructor. The instructor performs as the facilitator and provides the learning environment with activities that involve students talking through learning, rewriting what they learned and demonstrating what they experienced.

(2) *Constructive*, when students construct knowledge through exploration, reflection, and contribution within the learning environment to achieve full interpretation of this knowledge. They develop new innovations and ideas through their new knowledge [20].The Instructor's role is to design the instructional strategy to be constructive

that enable students to evaluate alternative solutions to problems as a mean of testing and reflecting their understanding.

(3) *Intentional*, when students are self-motivated and actively articulate their learning goal. They are willing to think and learn more to fulfill some goals [17]. They are accountable for their own learning and dynamically monitor their own progress during their study. They may able to utilize technologies to represent and get better understandable about new knowledge that they have constructed.

(4) *Authentic*, when instructors present real-life problems and challenging learning tasks and provide learning environments that offer expert thinking and access to different levels of expertise.

(5) *Cooperative*, when students collaborate and help each other to solve problems and achieve understanding. They communicate and work together within their group. In order to avoid biases, the instructor arranges the students in heterogeneous groups, in sizes of two to several people, in order for them to solve a problem.

Previous work by Yunianta *et al*., describes the Moodle e-learning activities undertaken in our courses [21]. In this work, we extend these descriptions by listing the e-learning actions. We agree that some of e-learning actions play an important role in affecting the students' e-learning usage. These e-learning actions are: adding, updating, talking, and discussing. Table 1 lists twenty one Moodle e-learning activities and actions available for the instructor and students. We realize that the actions offered to the instructors are different from those offered to students, and the activities that students can perform are dependent on the activities set by the instructor. For example, the instructor is allowed to add and update the assignment, as well as to update the grades in assignment activity, but not the students. The instructor may also give permission to the students to resubmit assignments or allow them to view the feedback. Therefore, we can conclude that the activity that students can perform is dependent to the activity set by the instructor.

Yunianta *et al*., [21] have successfully mapped the meaningful learning characteristics identified above with the students' activities of Moodle e-learning as shown in Table 2. A value of "1" means that the activity has some relation with the meaningful learning characteristics. A value "0" means that there is no relation between the activity and the meaningful learning characteristics. These findings are valuable to us in order to identify which activities have good impact on meaningful learning. To the sum of all the entries for an activity determines the proposed weight for each e-learning activity in relation to the meaningful learning characteristics.

Table 1 Moodle e-learning activities and actions

	Activity	Description	Action by Instructor	Action by Students
1.	Assignment	Instructor can communicate tasks, collect work and provide grades and feedback from the students. Student can type text directly into e-learning or submit any digital content (files), including word-processed documents, spread sheets, images, audio and video clips.	Add, Update, Update grades, Upload, View, View all	Upload, View, View all
2.	Blog	Blogs is a form of online journal that are organized as a chronological series of postings created by the user of the blog (i.e. student or instructor). Moodle allows the user to register his/her external blogs, so that entries are automatically included in their Moodle blog.	Create, Edit Entries, Edit External blogs, Search, View	Create, Edit Entries, Edit External blogs, Search, View
3.	Calendar	The calendar displays events, deadlines, times for other activities such as the user events, the assignment or quiz deadlines, the chat time etc.	Add, Edit, Delete, View	Add, Edit, Delete, View
4.	Chat	The chat activity allows participants to have a real-time synchronous discussion in a Moodle course. Users are able to manage and review the chat discussions.	Add, Talk, View	Talk, View, View all
5.	Choice	A choice activity allows the instructor to ask a question and specifies a choice of multiple responses. It can be useful as a quick poll to stimulate thinking about a topic. It also allows the class to vote on a direction for the course; or to gather research consent.	Add, Choose, Report, Update, View, View all	Choose, Choose again, View, View all
6.	Course	Courses are the places where instructor adds learning materials and re-organise them according to his/her own needs.	Add, Edit, Delete, View	View
7.	Forum	The forum activity module enables participants to have asynchronous discussions i.e. discussions that take place over an extended period of time. An instructor can allow files, such as images or videos, to be attached to forum posts. Forum posts can be rated by instructors or students (peer evaluation). Ratings can be aggregated to form a final grade which is recorded in the grade book.	Add discussion, Delete discussion, Add post, Delete post, Update post, User report, Subscribe, Unsubscribe, View discussion, View Forum	Add post, Delete post, Search, view Subscribe, Start tracking, Stop tracking

	Activity	Description	Action by Instructor	Action by Students
8.	Feedback	Feedback enables the instructor to create a custom survey for collecting feedback from participants using a variety of question types including multiple choices, true/false or text input.	Add, Update, View, View all	Start complete Submit, View, View all
9.	Glossary	Glossary can be used collaboratively to create and maintain a list of definitions or concepts or to collect and organize resources. The entries can be put in categories and can be searched or browsed.	Add, Update, Add entry, Update entry, View, View all	Add entry, Update entry, View, View all
10.	Journal	Journal allows the instructor to ask students to reflect on a particular topic. The students can edit and refine their answer over time.	Add, Update, View, View responses	Add entry, Update entry
11.	Label	A label serves as a spacer on a Moodle course page. It can be used to add text, images, multimedia or code in between other resources in the different sections. It is a very versatile resource and can help to improve the appearance of a course if used thoughtfully.	Add, Update	Nil
12.	LAMS	LAMS stands for Learning Activity Management System and instructor can use it for designing, managing and delivering online collaborative learning activities. These activities can include a range individual tasks, group works and class activities based on content and collaboration.	Add, Update, View, View all	View, View all
13.	Notes	Notes allow the user to attach information about a user, for example an instructor may attach a note to specific	Add, Update, View	Add, Update, View
14.	Quiz	The Quiz activity module allows the instructor to design and build quizzes consisting of a large variety of question types, including multiple choices, true-false and short answer questions. The instructor can choose when and if hints, feedback and correct answers are shown to students.	Add, Edit Questions, Update, Preview, Close/Continue/Attempt, Report, View, Manual Grading	Attempt, Continue/Close Attempt Review, View, View All
15.	Resource	Resources are files or link that support learning. Instructors can add a range of resources types to their course.	Add, Update, View, And View All.	View, View all
16.	Role	Role allows the instructor to assign permission to specific users in specific context. The combination of roles and context define user's ability to do something on any page.	Assign, Unassigned	Nil
17.	Survey	Survey lets the instructor gather data from students to learn about his/her class and reflect on his/her own teaching.	Add, Update, Submit, View All/Form/Graph	Submit, View, View All
18.	Upload	Upload the facility in the e-learning system to add/attach files.	Upload,	Upload
19.	User	User is the activity to update user profile.	Update, View	Update, View
20	Wiki	A collection of web pages that anyone can add to or edit. A wiki is a collection of collaboratively authored web documents and makes a good tool for group work	Add, Edit, Bogus, Info, Links, Update, View, View All	Bogus, Edit, Info, Links, View
21	Workshop	Workshop is a peer assessment activity with many options. Student can submit their work via online tools. Students are given the opportunity to assess one or more of their peers' submissions.	Add, Edit, Update, Grading, View, View All	Submit, View, View All

Table 2 The proposed weights for meaningful activities [17]

List	Activities	Active	Constructive	Intentional	Cooperative	Authentic	Weight
1	Blog	1	1	1	1	1	**5**
2	Discussion Forum	1	1	1	1	1	**5**
3	Lams	1	1	1	1	1	**5**
4	Wiki	1	1	1	1	1	**5**
5	Chat	1	1	1	1	0	**4**
6	Glossary	1	1	1	1	0	**4**
7	Workshop	1	1	1	1	0	**4**
8	Quiz	1	1	1	0	0	**3**
9	Assignment	1	1	1	0	0	**3**
10	Feedback	1	1	1	0	0	**3**
11	Journal	1	1	1	0	0	**3**
12	Notes	1	1	1	0	0	**3**
13	Choice	1	1	1	0	0	**3**
14	Survey	0	1	1	0	0	**2**
15	Course	0	0	1	0	0	**1**
16	Resource	0	0	1	0	0	**1**
17	Upload	0	0	1	0	0	**1**
18	User	0	0	1	0	0	**1**

List	Activities	Active	Constructive	Intentional	Cooperative	Authentic	Weight
19	Calendar	0	0	0	0	0	**0**
20	Label	0	0	0	0	0	**0**
21	Role	0	0	0	0	0	**0**

In addition, Yusof *et al.*, [22] have introduced score weighting for meaningful e-learning actions that show active or passive participation. A weight of "3" is given to a student- who is active in constructing knowledge such as creating a new page. A weight of "2" is given to a student- who makes changes to existing work for improvements, and a weight of "1" is given to a passive student who only views and browses a page. In this work, we group Moodle e-learning actions into three categories: (1) creating new data or information; (2) updating data/information for improvements; and (3) viewing or deleting data/information. Weights are assigned to these actions by category i.e. "3" for creating, "2" for updating/improving and "1" for viewing. Figure1 shows the proposed weights of the e-learning actions based on the meaningful learning characteristics. Furthermore, these weights are used to calculate the action score, as well as to measure the index of the meaningful learning characteristics of e-learning usage.

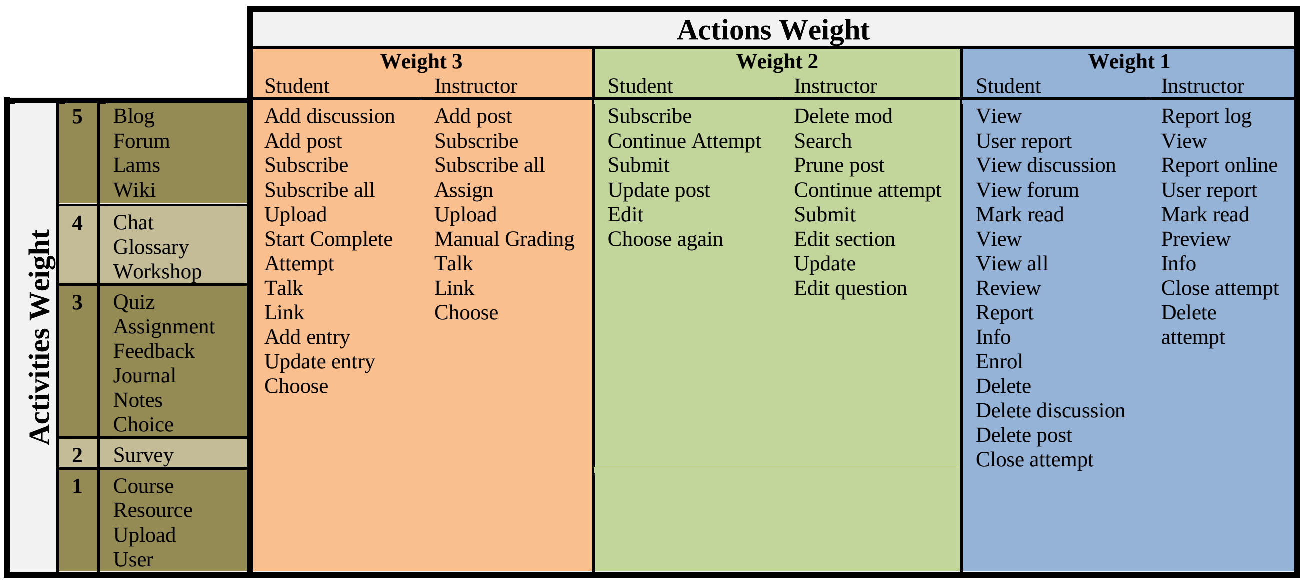


Figure 1 The proposed weights for meaningful action

3.0 METHODOLOGY

Students' behavior in the e-learning system can be described as students' interaction during online learning [23]. This argument was reinforced by the work done by Bhuasiri *et al.*, who stated that e-learning has no value without students' usage in the e-learning systems [24]. Three kinds of possible interactions in learning activities are: students with instructor(s), students with materials, students with students [25]. The more students perceive interaction with others, the higher the e-learning satisfaction [23]. In the process of online learning, students are able to choose which activity they prefer in order to fill up the requirement of their study. Chen *et al.*, suggested that students' behavior in e-learning usage can be divided into three levels, namely low, intermediate, and advanced [26]. Moreover, most scholars have agreed that students' learning quality can be determined by evaluating and analyzing their learning activities [27-29].

3.1 Cluster of Meaningful E-learning Usage

The aim of this paper is to cluster the students into different levels of e-learning usage based on meaningful learning characteristics using the

clustering method. The cluster definitions in this paper are:

High cluster group: *Cluster group has <u>high score</u> for e-learning usage of meaningful activities and actions.*

Medium cluster group: *Cluster group has <u>medium score</u> for e-learning usage of meaningful activities and actions.*

Low cluster group: *Cluster group has <u>low score</u> for e-learning usage of meaningful activities and actions.*

3.2 Clustering Procedures

Figure 2 illustrates the procedures for the clustering of e-learning usage based on meaningful learning characteristics. It comprises four stages: (1) data log observation - to define activities and action that occurs during class; (2) assign meaningful weight – (3) meaningful learning usage calculation – to determine the weights of meaningful activities and actions; (4) pre-processing analysis - to normalize the data and to eliminate inconsistent data; (5) clustering analysis – to define the cluster center (centroid) and identify clustering.

First, we observe the data log and sort it in ascending order according to the type of e-learning activities. Next, we save it in a record which consists of three fields: the activity name, the action name, and the number of access hits. Then, we calculate the action score for each e-learning activity. The score is measured based on the action weights as listed in Table 3 by using Equation (1).

$$\textbf{Action Score} = \sum_{i=1}^{a} \boldsymbol{h_i} * \boldsymbol{w_i} \qquad (1)$$

In Equation (1), i is an action in Moodle activities, a is the number of actions, h_i is the number of the access hits for each action, and w_i is the weight for each action as proposed in (Table 2). Next, based on the action score (in Equation (1)) and the activity weights (in Table 2), the instructors' and students' meaningful indices are calculated by Equation (2). J is an activity in Moodle e-learning, k is the number of activity, w_j is the weight for each activity as proposes in Table 2 and n is the total students.

$$\textbf{Meaningful Index} = \sum_{j=1}^{k} \frac{(Actions\ Score) * w_j}{n} \qquad (2)$$

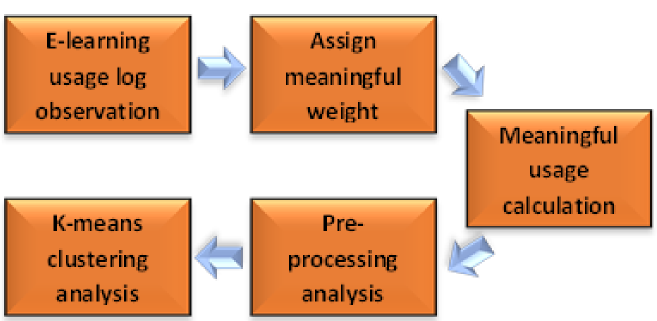


Figure 2 Research Procedures

3.3 Data Collection

The case study is obtained from the Computational Intelligence Course (Course Code: SCJ4553-01) at the Software Engineering Department, Universiti Teknologi Malaysia (UTM). This course was conducted in Semester 1, year 2012-2013 and pursued for 19 weeks i.e. from September 10, 2012 until January 20, 2013. There are 37 students and 1 lecturer enrolled in this course. Both the lecturer and students are using the Moodle e-learning system and are involved in some of the e-learning activities. In this study, we observed the e-learning data to identify the activities and actions performed by the students during the semester. The students' e-learning data log contains the following information: *course code, time, user IP address, user full name, action, and information*. Table 3 shows a part of the data sample.

3.4 Empirical Validation

A common problem faced by higher institutions is whether the variety of e-learning approaches contribute a significant effect to learning goals [30]. Achievement in the course is still regarded as a good measure of achievement of learning goals. Thus, this paper will present an empirical analysis to validate the relation between meaningful e-learning activities and actions (hits) with the learning outcomes (class final score). The empirical validation based on hypothesis: (i) the hypothesized relationship between the meaningful activities and actions implementation on e-learning system and the achievement of learning outcomes. In purposes to this validation, the data sample has been verified on the 37 students who were implemented e-learning scenario. Moreover, the statistical assumptions for parametric inference have been considered as a validation method.

3.5 K-Means Clustering Methodology

Clustering is a method in several fields of study such as data mining [31], statistical data analysis [32], compression [33], and pattern recognition [34]. The main concept of clustering is grouping (clustering) a set of data which have similar features.

In this work, we assume that there are n e-learning activities to be considered in defining the cluster of students' e-learning usage and the sample consists of $\{S_1,\ldots,S_X\}$, in which each sample consists of m characteristics, can be described as $S_i=\{S_{i1},\ldots,S_{im}\}$ and $i=(1,\ldots,n)$. Therefore with n e-learning activities and m characteristics, the data samples need to be normalized, prior to the clustering process (pre-processing phase). Normalization for s raw data is defined by $r_{ij} = \frac{s_{ij} - s_{i\,min}}{s_{i\,max} - s_{i\,min}}$ where $S_{i\,max}$ is the maximum sample, $S_{i\,min}$ is the minimum sample and r_{ij} is the standardized value with $0 \le r_{ij} \le 1$ [26]. For the K-Means method, we follow the algorithm suggested by Forgy [35] as depicted in Algorithm 1. For each K cluster, we need to define the centroid and the set of data which is closest by measure the distance of data to the centroid (d()) by using Euclidian distance. The K clusters are clusters we assigned: high, medium, and low; and each cluster have a centroid (c) and x points appointed to students.

Algorithm 1 K-Means clustering algorithm

Input: x points, distance function d(),K cluster

1. Set K cluster
2. Calculate d(each point x, each centroid c)
3. Find closest c(x) for each x
4. Assign x ⊆ c
5. While x ≠ 0, repeat step 2

Table 3 Part of Data Sample

Course	Time	IP address	User	Action	Information
SCJ4553-01	2013 January 23 11:52	161.139.101.201	User full name	forum view discussion	Group Leader
SCJ4553-01	2013 January 23 11:52	161.139.101.201	User full name	forum view forum	Team Members
SCJ4553-01	2013 January 23 11:51	161.139.101.201	User full name	course view	Group members
SCJ4553-01	2013 January 23 11:48	161.139.101.201	User full name	forum view discussion	Hello My Team Members
SCJ4553-01	2013 January 23 11:47	161.139.101.201	User full name	forum view discussion	Leader

4.0 RESULTS AND DISCUSSION

The analysis has been conducted and some findings have been obtained. The following sub-sections are describing the data log observation result, pre-processing result, and clustering result.

4.1 Result of Data Log Observation

The observation of the log file focuses on the access hits that indicate the frequency of the activities and actions that were gained throughout the semester. For the purpose of normalization, we filter only the activities that achieved more than 100 hits. In this observation, there are seven activities to be considered for further process: *discussion forum, wiki, assignment, feedback, course, resource, and user*. The *discussion forum* activity reaches the highest hits with the total of 4742 hits, followed by the *course* activity with 4644 hits, *resource* activity with 4093 hits, *wiki* activity with 3733 hits, *feedback* activity with 960 hits, *assignment* activity with 753 hits and finally the *user* activity with 302 hits (see Figure 3).

4.2 Result of Preprocessing Analysis

The clustering process is then executed based on data log observation results. The pre-processing phase is conducted first in order to reduce the effect of differences between variables. This normalization process is accomplished by descriptive analysis. During the process, three sets of data have been recognized out of the range, namely the set for students 2, 8 and 37 as show in Table 4. Thus, only 34 data sets are left to be continued in the clustering process. Table 4 shows the pre-processing results of the z-scores for the seven activities that were observed and highlights the out-of-range students, whom are Student 2, Student 8 and Student 37.

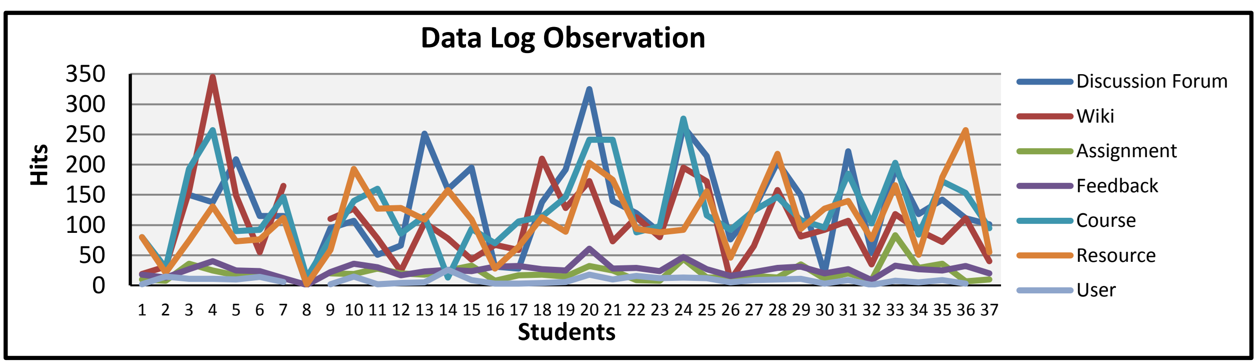


Figure 3 Result of data log observation

Table 4 Result of preprocessing analysis

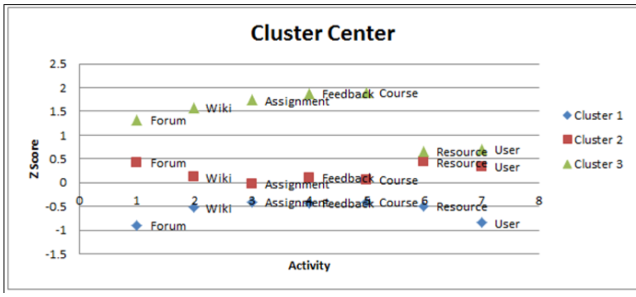
Student	zForum	zWiki	zAssignment	zFeedback	zCourse	zResource	zUser
1	-1.31175	-1.28329	-0.75627	-0.77058	-0.72558	-0.53678	-1.20305
2		-1.10147	-0.89483	-1.25547	-1.53862	-1.57102	1.15638
3	0.24535	0.79254	1.04493	0.10222	1.07587	-0.64196	0.4304
4	0.08427	3.65627	0.28288	1.36293	2.09616	0.35722	0.4304
5	1.03732	0.68647	-0.27133	-0.09174	-0.56616	-0.65949	0.24891
6	-0.22447	-0.73782	-0.40989	-0.18871	-0.53427	-0.6069	0.97488
7	-0.22447	0.9289	-0.89483	-1.35244	0.3266	0.02416	-0.47707
8	-1.75472			-2.4192	-1.7937	-1.90407	
9	-0.49293	0.09554	-0.0635	-0.38267	-0.75746	-0.9049	-1.20305
10	-0.33185	0.35313	-0.13278	0.97502	0.23094	1.44405	1.15638
11	-1.08356	-0.38932	0.49071	0.39315	0.54979	0.2871	-1.20305
12	-0.88221	-1.20753	-0.0635	-0.86756	-0.62993	0.30463	-0.84006
13	1.6011	0.00463	-0.20206	-0.28569	-0.16761	-0.02843	-0.65857
14	0.36616	-0.38932	0.28288	0.00524	-1.7937	0.83052	3.15282
15	0.8494	-0.91964	0.8371	-0.18871	-0.50239	-0.02843	0.06741
16	-1.35202	-0.556	-0.89483	0.49013	-0.885	-1.44831	-1.02155
17	-1.39229	-0.67721	-0.27133	0.58711	-0.31109	-0.81725	-1.02155
18	0.08427	1.61074	-0.20206	0.10222	-0.18355	0.04169	-0.84006
19	0.80913	0.36828	-0.40989	-0.09174	0.3266	-0.37901	-0.47707
20	2.59442	1.05012	0.76782	3.39946	1.84109	1.61934	1.70086
21	0.11111	-0.46508	0.28288	0.1992	1.84109	1.12852	0.24891
22	-0.15735	0.141	-0.82555	0.29617	-0.59804	-0.29137	1.33787
23	-0.5869	-0.35902	-0.89483	-0.18871	-0.43862	-0.39654	0.6119
24	1.76218	1.38346	1.59914	2.04177	2.39906	-0.32643	0.79339
25	1.10444	1.03497	-0.54844	0.10222	-0.15166	0.79546	0.6119
26	-0.74798	-1.43481	-0.54844	-0.96453	-0.53427	-1.13278	-0.65857
27	-0.07681	-0.5863	-0.34061	-0.38267	-0.02413	0.32216	0.06741
28	0.97021	0.82284	-0.54844	0.29617	0.34254	1.88228	0.24891
29	0.23192	-0.34387	0.97565	0.49013	-0.2792	-0.29137	0.4304
30	-1.49968	-0.17719	-0.687	-0.57662	-0.47051	0.2871	-1.02155
31	1.21182	0.05009	-0.0635	0.10222	0.94834	0.51499	0.06741
32	-1.04329	-1.04086	-0.82555	-1.64338	-0.35891	-0.58937	-1.38454
33	0.83597	0.21676	4.30094	0.68409	1.23529	0.97075	-0.11408
34	-0.1842	-0.19235	0.55999	0.10222	-0.66181	-1.04513	-0.65857
35	0.13796	-0.48024	1.04493	-0.09174	0.74109	1.19863	0.06741
36	-0.27816	0.11069	-0.9641	0.58711	0.43819	2.56593	-1.02155
37	-0.41239	-0.9651	-0.75627	-0.57662	-0.48645	-0.97502	

4.3 Result of Clustering Analysis

Since there are seven activities to be observed, the K-Means clustering process iterates seven times to define the cluster center for each activity. Figure 4 shows the final cluster center result (Zscore) for seven activities in each cluster level and Figure 5 shows the final clustering analysis, which presents the final Zscore of members in each cluster level.

The clustering result also shows the cluster group for each member. The high cluster group consists of four members who are Students 4, 20, 24, and 33. The medium cluster group consists of eighteen members who are Students 3,5,6,10,13,14,15, 18, 19, 21, 22, 25, 27, 28, 29, 31, 35, and 36. The low cluster group consists of twelve members who are Students 1,7,9,11,12,16,17,23, 26, 30, 32, and 34.

It can be observed that the students, who are actively using the *feedback, wiki,* and *forum* activities, receive high scores and are grouped in the high cluster level. Besides the meaningful activities, the actions in each activity also give strong effect to the clustering result. The clustering result also illustrates that the members in high cluster group have actively implemented the *active, collaborative* and *constructive* activities, which we claim as the meaningful learning characteristics. In the medium cluster group, the students achieved average meaningful score. After careful investigation, we found out that these students were involved in some meaningful activities and actions. On the other hand, there are twelve students in the low cluster group who need to be paid more attention and given support by the instructor.



	Cluster 1 Low	Cluster 2 Medium	Cluster 3 High
Zscore(Forum)	-0.90011	0.42731	1.31921
Zscore(Wiki)	-0.52443	0.11406	1.57665
Zscore(Assignment)	-0.40412	-0.02502	1.7377
Zscore(Feedback)	-0.43116	0.10761	1.87206
Zscore(Course)	-0.40807	0.06355	1.8929
Zscore(Resource)	-0.49734	0.43318	0.65522
Zscore(User)	-0.84006	0.33965	0.70264

Figure 4 Result of cluster centre (centroid)

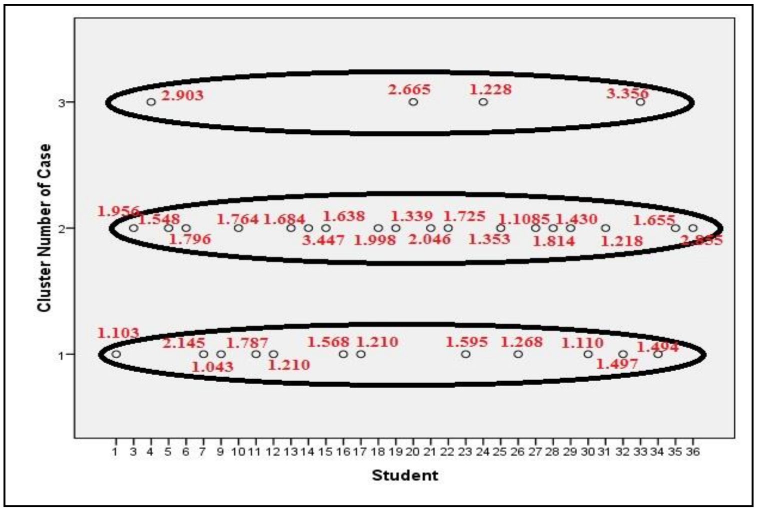


Figure 5 Result of final cluster membership

In a deeper investigation of the clustering result, specifically towards the original access hits of the students in the high cluster group, we observe that student 4 has the highest access hits for the *wiki* activity (345 hits) while Student 20 has highest access hits for the *forum* activity (328 hits). These two activities are noted as having a high potential for meaningful learning activities and are given a high weight score of 5. Moreover, Student 20 has the highest access hits on *added page for wiki* (20 hits) while Student 4 has the highest access hits on *edited in wiki page* (104 hits). For the *forum activity*, we recognize that Student 20 has the highest hits for *added discussion forum activity*. The next highest access hits for the *forum activity* are Students 24, 33, and 4. These actions indicate that Student 4 and 20 have performed collaborative and constructive activities, and they intend to stimulate their colleagues to interact through the topic. In line with the *discussion forum activity*, all members in the high cluster group actively *added comments on the wiki page*. Since the weight for *add action* is 3 and *edit action* is 2, it makes sense that Students 4, 20, 24 and 33 are included in the high cluster group. Another interesting case is for *add post* for *forum activity,* in which Student 4 has only 30 hits compared with Student 13 with 81 hits or Student 15 with 69 hits for this action. Yet, the final clustering result still included Student 4 as a high cluster member. In this matter, we found a reasonable cause when we considered *wiki* activity. Student 4 had *edited wiki page* with 104 hits, while Student 13 had 32 hits and Student 15 had 6 hits. This is how our proposed mapping weights of activity and action are handy.

We then take a deeper look on the medium cluster group. Interestingly, we found out that Student 25 has higher access hits on *wiki activity* (172 hits) compared to Student 33 (118 hits) who is the member in the high cluster group. We try to investigate why this student is in the medium cluster group instead of the high cluster group. We notice that the type of actions that Student 25 has performed are *view wiki* (123 hits), *edit page* (40 hits), *add a new page* (3 hits), and *add comments* (6 hits). On the other hand, the type of actions that the Student 33 has performed are *view wiki* (62 hits), *edit page* (30 hits), *add a new page* (12 hits), and *add comments* (14 hits). This scenario will strengthen our argument that high access hits of e-learning usage does not necessarily means that the student is part of high cluster group. Instead, a student is grouped in a high cluster group if he/she has high access hits in the active actions of the meaningful e-learning activities (see **Appendix**).

We realize that the majority of the students in low cluster group have high access hits in the *view action* for almost all activities. For example Student 7 with overall 583 hits, yet most of actions performed is *view (course view* 145 hits, *resource view* 112 hits, and *wiki view* 93 hits). This action indicates that the student has the intention towards e-learning instead of active participation for meaningful learning. Therefore, we can conclude that the actions that contribute to meaningful learning activities are: *add a discussion forum, add new wiki page, edit or post discussion forum* and *comments* in wiki page. These actions indicate active, collaborative, and constructive meaningful learning activities.

4.4 Result of Empirical Validation

We have succeeded to grouping students into three level of meaningful e-learning usage cluster; the next step is to validate the cluster result. In regard to contribute to learning outcomes, in this section we reveal the interdependency of e-learning usage with learning outcomes measured by the final score achieved by students at the end of course. Figure 6 shows ratio of e-learning usage as number of hits and final score while Table. 5 incorporate with the clustering result. This summary surprisingly illustrates that students in the highest cluster group were not consist in the top three of the student's final score. As an empirical validation the Pearson correlation was used, Table 6 indicates the correlation between e-learning hits and final score. As perceived sig= 0.041 (sig > 0.05), then the hypothesized relationship between the meaningful activities and actions implementation on e-learning system and the achievement of learning outcomes is empirically validated. However, the *Pearson* correlation (*r*) indicates as 0.352 which somehow outlying from 1 point. This can be explained by the fact, even though the e-learning usage has correlation to the learning outcome yet it does not bring significant impact. It makes sense since enormous numbers of students are included in the low level cluster group.

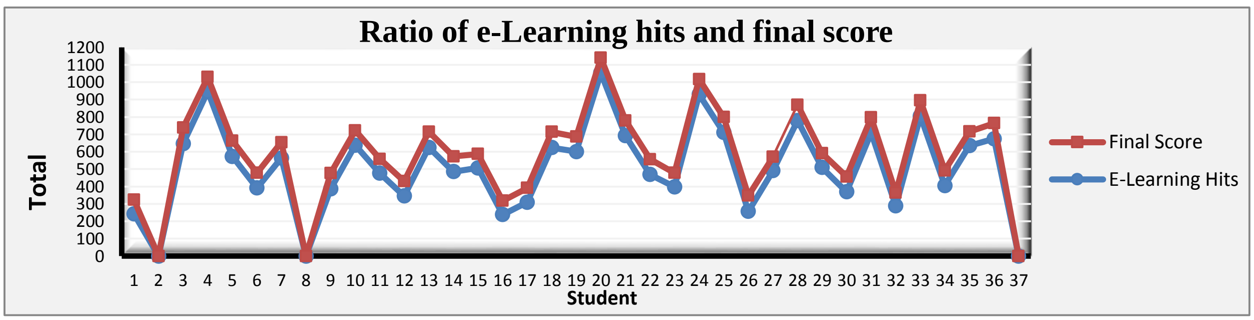


Figure 6 Ratio of e-learning hits and final score

Table 5 Summary of e-learning usage, final score, and clustering result, N=34

Student	E-Learning Hits	Final Score	Cluster	Student	E-Learning Hits	Final Score	Cluster
3	647	**91**	**2**	24	930	**87**	**2**
28	779	**91**	**2**	31	710	**87**	**2**
5	573	**90**	**2**	34	405	**87**	**3**
7	564	**90**	**3**	10	637	**85**	**3**
9	386	**90**	**2**	12	345	**85**	**2**
13	625	**90**	**2**	19	601	**85**	**1**
18	624	**90**	**2**	4	947	**82**	**1**
26	257	**90**	**2**	11	476	**82**	**3**
33	805	**90**	**3**	17	309	**82**	**2**
36	674	**90**	**2**	29	509	**82**	**3**
25	710	**89**	**3**	1	243	**81**	**3**
14	485	**88**	**2**	35	635	**81**	**2**
30	369	**88**	**3**	15	507	**80**	**3**
6	391	**87**	**2**	16	238	**80**	**3**
20	1053	**87**	**2**	23	398	**80**	**1**
21	692	**87**	**2**	27	491	**79**	**2**
22	469	**87**	**3**	32	288	**76**	**1**

Table 6 Interdependence of meaningful e-learning indicators and learning outcomes, N=34

	Mean	Std. Deviation	Kolmogorov-Smirnov Z	Pearson Correlation	Assimpt. Sig (two-tailed)	Exact Sig
E-learning Hits	552.12	205.694	0.200			
Final Score	85.76	4.171	0.001			
Summary of interdependence				0.352	0.05	0.041*

**correlation is significant at the 0.05 level (two-tailed)*

5.0 DISCUSSION

The aim of this paper is to analyse students' e-learning usage based on meaningful learning characteristics (i.e. *active, authentic, cooperative, collaborative, and intentional*). We define the students' behaviour by their interest of learning activities and actions during online learning and determine whether the students have successfully achieved meaningful online learning. In summary, we found out that student with high access hits on the actions of creating or improving data and/or information such as *add, post, update, edit, add a comment,* and *add a page* are included in the high cluster group. On the contrary, students with high access hits on the view actions for all e-learning activities are included in the low cluster group. These findings are supported by earlier research, which stated students' interaction in online learning can be viewed as students' behaviour [23]. In addition, activities with high interactions are found to be more valuable as suggested by Bhuasiri *et al*., who stated that the more students interact in online learning, the more valuable the learning process will be [20].

Besides that, the students who are included in the high cluster group have conducted activities and actions which display meaningful learning characteristics. This implies that they successfully achieved meaningful online learning. They have been succeeded performed certain meaningful activities and actions such as adding post in the discussion forum, it shows that the student actively participate in the topic discussion. By adding post or reply the post, they share their opinions, solutions, knowledge or ideas for certain problems and allow others to give feedbacks. This distance interaction builds up the collaborative learning by sharing the tasks to review certain topic and then share their invention to others. In addition, it also build up the constructive learning by interpret their solutions for problem solving. This result supports our argument in which certain activities and actions in e-learning can have a great impact to meaningful learning. These activities and actions are given the meaningful weights to show the significance impact to the learning process as show in Table 2 and Figure 1. Instructors have to employ these as learning medium, resources deliverable, individual or group tasks, or distance communication. Moreover these activities and actions are support the active, constructive, cooperative, intentional and authentic learning. By adding post, adding comments, and adding new pages, they act out meaningful learning, as well. These actions conform to Bonwell & Eison who defined it as actively 'doing things' and thinking what they are 'doing' [36]. Meanwhile, the updating and adding comments denoted that students raise issues or bring up new opinions [37]. This also shows that they are cooperative and collaborative among them in order to solve the problems given by the instructor [38].

This work may assist us to determine students with high, medium, and low interest on meaningful activities and actions during online learning. Therefore, with suitable e-learning activities and actions, online learning environments are able to designate and implement a high quality online experience [39]. Based on the results in this paper, this happened when instructor and students succeeded to perform the meaningful online learning, means that they are succeed to gather the knowledge or perform certain learning activities and tasks through online learning. The clustering results means to promote meaningful-based online learning and to discover e-learning usage. To achieve this, instructors are suggested to come out with an efficient plan and strategy to perform online learning activities and to take advantages of computer usage in the education process.

This paper brings an approach of data mining technique to analyze e-learning log file. The results give implication for scholar users. For students and parents, the impact is they are able to see the performance result during online learning. For instructor, this is as an initial analysis to predict students' achievement in the course and to promote more e-learning activities and actions to the students. For e-learning administrator and university stakeholder, this is to validate the efficiency of e-learning implementation towards learning process and outcomes. This findings shows that applied data mining technique to investigate students' online learning performance bring meaningful result, because it is able to engage learning pedagogy (i.e. meaningful learning characteristics) and gives a meaning to the e-learning log file by showing the usage cluster based on this pedagogy.

6.0 CONCLUSION

This paper applies a particular cluster method to observed students' e-learning usage. The principle objective is to cluster the students' usage of activities and actions in e-learning based on meaningful learning characteristics. The clustering result shows only a small number of students have successfully applied meaningful activities and actions in the e-learning system. Moreover, we found that even the e-learning usage has correlation to the learning outcome yet it does not bring significant impact. It has to be said that the collaboration of the e-learning existence not meaningful used. The recommendation assign for instructor to enrich the learning materials inside e-learning, such as to provide an online discussion with a certain case study and let the students to discuss in the forum discussion. Encourage them to share the ideas, opinions, or issues. Assign students to implement the subject materials to the real-life problem, and share the result in the e-learning wiki activity. These online activities bring students to do high order thinking, collaborative, constructive and problem solving tasks through online activities and eventually instructor could perform assessment based on discussion result. This experimental result can guide instructors to encourage more interaction with and between students during online learning, and also to select activities which are more active and collaborative in designing the learning strategies. Since there are varieties of learning activities in the e-learning system it is may be applied in all fields of study. In future work, we would like to compare the instructors' activities with the students' e-learning usage for meaningful learning by using other clustering methods.

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Appendix

E-learning Usage Hits and Cluster Level Result

Activity	Action	CLUSTER/STUDENT																																		
		High				Medium																				Low										
		4	20	24	33	3	5	6	10	13	14	15	18	19	21	22	25	26	27	28	29	25	31	35	36	1	7	9	11	12	16	17	23	30	32	34
Wiki	edit	104	36	50	30	44	137	18	30	32	14	6	54	30	14	26	40	2	12	52	14	40	10	28	18	3	76	28	22	8	24	12	18	34	10	24
	view	223	122	133	62	109		28	91	69	55	28	153	92	50	80	123	4	53	106	64	123	94	38	81	16	93	76	47	16	43	47	44	43	25	52
	add page	12	12	3	12	3	9	6			6	3	3	6		3	6	3			3	6		6				6	3				6	12		15
	comments	6	3	9	14		3	3		3	3	6			9	3	3					3	3		12				6				12	3		
	TOTAL WIKI	345	173	195	118	156	149	55	121	104	78	43	210	128	73	112	172	9	65	158	81	172	107	72	111	19	169	110	78	24	67	59	80	92	35	91
Forum	add post	30	81	66	33	30	54	30	6	81	42	69	24	30	10	18	39	24	21	63	39	39	24	18	30	12	21	24	9	15	9	1	15	6	12	30
	add discussion	3	12	15	9	3	6	3	6	6	6	9	3		9	3	12	3	6	6	6	12	3	6	3		12		3	3			3		6	3
	update post	4	8	14	4	4	10	10	16	18	4	2	14	10	4	8	12		8	18	10	12	18	6			2	6	4	6	4				2	4
	view discussion	71	140	95	83	68	95	44	44	101	79	67	64	78	70	59	94	30	50	81	47	94	108	79	47	14	44	42	18	28	11	9	39	9	17	55
	view forum	29	86	73	65	45	43	28	35	44	28	46	34	74	40	32	57	19	41	36	47	57	69	33	31	8	36	23	17	14	7	18	31	5	16	26
	user report	1																																		
	delete post		1				1			1																									1	
	search											2									13															
	TOTAL FORUM	138	328	263	194	150	209	115	107	251	159	195	139	192	133	120	214	76	126	204	162	214	222	142	111	34	115	95	51	66	31	28	88	20	54	118
Blog	view			1					1	1							1					1	1													
	TOTAL BLOG	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Assignment	submit	4	6	6	6	4	4	2	4	2	4	2	4	4	2	2	2	4	2	2	2	2	2	2	2	2	2	6	4	2	2	4	2	2	2	2
	view	16	22	29	6	30	9	12	13	15	17	29	12	7	22	6	8	5	12	10	20	8	15	32	4	6	5	11	22	16	5	9	5	8	6	2
	view submit form	5	4	9	3	2	4	1	2	1	4	2	2	4	1	1	3	4	2	1	3	3	3	2	1	2	1	3	2	2	1	4	1	1	1	5
	TOTAL ASSIGNMENT	25	32	44	15	36	17	15	19	18	25	33	18	15	25	9	13	13	16	13	25	13	20	36	7	10	8	20	28	20	8	17	8	11	9	9
Feedback	start complete	15	21	15	12	5	9	12	15	9	9	9	9	9	12	12	9	6	9	12	9	9	9	9	9	6	2	9	12	6	9	12	9	9	9	9
	submit	10	14	10	8	5	6	6	10	6	6	6	6	6	8	8	6	4	6	8	6	6	6	6	6	4	2	6	8	4	6	8	6	6	6	6
	view	15	26	22	13	17	10	6	11	8	11	9	12	10	8	9	12	6	7	9	16	12	12	10	17	8	8	7	10	7	16	12	9	5	8	12
	TOTAL FEEDBACK	40	61	47	33	27	25	24	36	23	26	24	27	25	28	29	27	16	22	29	31	27	27	25	32	18	12	22	30	17	31	32	24	20	23	27
Course	view	257	241	276	203	193	90	92	140	115	133	94	114	146	240	88	116	92	124	147	108	116	185	170	153	80	145	78	160	86	70	106	98	96	103	84
	recent														1									2			1							96		
	TOTAL COURSE	257	241	276	203	193	90	92	140	115	133	94	114	146	241	88	116	92	124	147	108	116	185	172	153	80	146	78	160	86	70	106	98	192	103	84
Page	view	16	31	28	28	22	3	14	16	16	16	12	17	21	24	6	13	10	9	14	15	13	23	13	15	9	15	8	14	12	10	3	14	7	12	10
	TOTAL PAGE	16	31	28	28	22	3	14	16	16	16	12	17	21	24	6	13	10	9	14	15	13	23	13	15	9	15	8	14	12	10	3	14	7	12	10
Resource	view	131	203	92	166	74	73	76	193	109	158	109	113	89	175	94	156	46	129	218	94	156	140	179	257	80	112	59	127	128	28	64	88	127	77	51
	TOTAL RESOURCE	131	203	92	166	74	73	76	193	109	158	109	113	89	175	94	156	46	129	218	94	156	140	179	257	80	112	59	127	128	28	64	88	127	77	51
URL	view	2	3	2	2	1	1		6	1	2	1	2	4	2	1	1	1		2	1	1	1	1	1	2			3	2	1	1	1	2	1	1
	TOTAL URL	2	3	2	2	1	1	0	6	1	2	1	2	4	2	1	1	1	0	2	1	1	1	1	1	2	0	0	3	2	1	1	1	2	1	1
User	view	6	13	8	6	2	8	14	3	4	14	6	4	6	7	6	7	5	3	10	4	7	4	8	3	1	5	2	2	2	3		3	3	1	5
	view all	5	5	5		9	2		12	1	12	3			3	10	5		6		7	5	5	1		1	1			2		3	9			
	update				2											2																				
	TOTAL USER	11	18	13	8	11	10	14	15	5	26	9	4	6	10	18	12	5	9	10	11	12	9	9	3	2	6	2	2	4	3	3	12	3	1	5
TOTAL HITS		965	1090	961	767	670	577	405	654	643	623	520	644	626	711	477	725	268	500	795	528	725	735	649	690	254	583	394	493	359	249	313	413	474	315	396