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Blended Learning Evaluation in Higher Education Courses

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Abstract

Although traditional learning was a necessity for centuries and distance learning is sometimes the only way for learning for many learners, the last two decades a supplementary mode to the other modes of learning emerged, the e-learning. However, the last few years, blended learning has dominated as the only mode which combines perfectly the advantages of the other modes of learning.

The role of educational content in blended learning is crucial. The key factor to success is high quality educational content, appropriate for learning and able to fulfill course educational aims and objectives. Most of the times it is not an easy task to give feedback to instructors about the online educational content. However, some course characteristics and students' actions may reflect the quality and quantity of the educational content.

This study evaluates the use of blended learning in TEI of West Macedonia with the use of structured questionnaires exposed to the learners. The learners express their attitude about how useful the blended learning is and how this blended means facilitates their studies. It proposes two variables Richness and Usefulness, taking into account statistics concerning the courses. These variables aim to help course instructors and administrators review course usage and find course weaknesses.

Keywords: Blended learning, evaluation, questionnaire, richness, usefulness

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1. Introduction

Traditional learning has been the staple for hundreds of years, from the very founding of higher education institutions (Dewey, 2009). Learners meet together in real time and in a specified location with the educator present. This educator centered approach is the predominant modality of instruction in higher education. Information and Communication Technologies (ICT) can be used to enhance the educational experience with the use of technology delivering the instruction and maintaining learner records.

Distance Learning is the evolution of correspondence courses since learners and educators are separated by time, location, or both in this model of instruction. The materials may be delivered to remote locations via print or ICT, but this form of instruction does not preclude the use of remote classrooms. This form of instruction may be

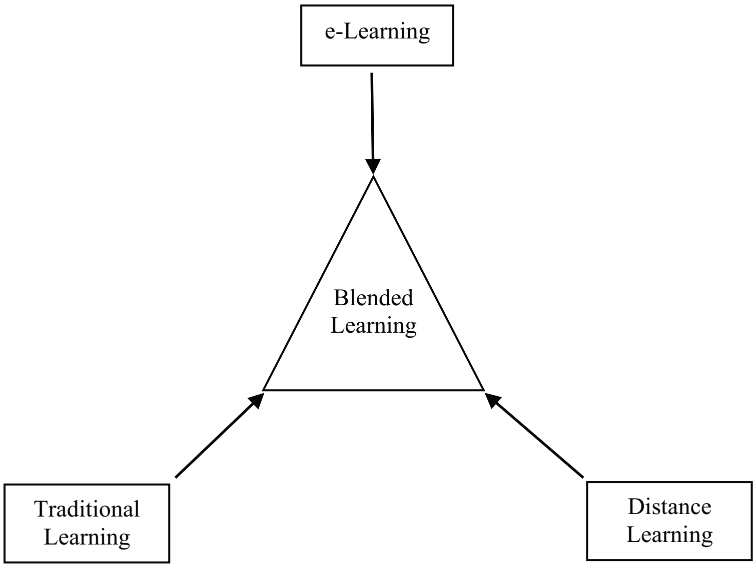

Figure 1: Modes of learning systems.

done synchronously or asynchronously. The emphasis of this mode of instruction is the separation of the learner from the educator and not the delivery mechanism [8].

E-learning had its beginnings in late 1994. E-learning describes the ability to electronically transfer, manage, support, and supervise learning and learning materials [17]. E-learning has been viewed as synonymous with web-based learning, Internet-based training, advanced distributed learning, web-based instruction, online learning and open/flexible learning (Khan, 2001). E-learning is the effective learning process created by combining digitally delivered content with learning support services [12]. Many authors have discussed the way in which e-learning can be used for the delivery of training, assessment, and support [4].

Learning Management Systems (LMSs) are software tools designed to manage user learning interventions and offer an extensive range of complementary functionality [6]. They are extensively used nowadays and they provide a variety of information and communication channels for the users [30]. Among the features they provide are the development, management, distribution, diffusion and presentation of the educational material as well as tools for the management of users and courses [5].

In the blended learning mode, parts of the instruction are delivered in a traditional format while other parts of it are delivered using ICT. It is this blending of the delivery modality that attempts to use the strengths of both formats to enhance the educational experience. The most used Blended Learning definition is the combination of online and face to face instruction [23, 26, 27, 34, 36]. Other studies [7], (Nor Azian 2015) also mention that blended learning is a popular learning approach in higher institutions and more and more universities are adopting blended learning (BL). Blended learning uses the tools of the provincial learning management system (LMS) to teach and support learning in a face-to-face class. Therefore, it combines traditional learning, distance learning and e-learning in such way, in order to produce high quality courses (fig. 1).

Statistics is a mathematical science concerning the collection, analysis, interpretation or explanation, and presentation of data (Freedman et al., 2007). It is relatively easy to get basic descriptive statistics from statistical software, such as SPSS. It is also used with educational data; this descriptive analysis can provide such global data characteristics as summaries and reports about learner's behavior [35].

It is not surprising that teachers prefer pedagogically oriented statistics (overall success rate, mastery levels, typical misconceptions, percentage of exercises tackled, and material read) that are easy to interpret. Applying descriptive statistics to educational data is the easiest way that educators prefer [37]. Sometimes, teachers find the fine-grained statistics in log data too cumbersome to inspect or too time-consuming to interpret. Statistical analysis of educational data (logs files/databases) can tell us things such as: where students enter and exit, the most popular pages, the browsers students tend to use, and patterns of use over time (Ingram, 1999); the number of visits, origin of visitors, number of hits, and patterns of use throughout various time periods [9]; number of visits and duration per quarter, top search terms, and number of downloads of e-learning resources [10]; number of different pages browsed and total time for browsing different pages [13]; usage summaries and reports on weekly and monthly user trends and activities [18]; session statistics and session patterns [21]; the time a student dedicates to the course or a particular part of it [21]; the learners' behavior and time distribution and the distribution of network traffic over time [38];

Statistical analysis is also very useful to obtain reports assessing how many minutes the student has worked, how many minutes he has worked in a particular day, how many problems he has resolved, and his correct percentage, our prediction of his score, and his performance level [2]. Information visualization uses graphic techniques to help people to understand and analyze data (Mazza, 2006); mean values of attributes analyzed in data to measure mathematical skills [39]; and higher education student-evaluation data [11].

Providing feedback for supporting instructors is a very crucial feature for any learning system. The objective sare to provide feedback to support course educators/teachers/administrators in decision making (about how to improve students' learning, organize instructional resources more efficiently, etc.) and enable them to take appropriate proactive and/or remedial action [16]. It is important to point out that this task is different than data analyzing and visualizing tasks, which only provide basic information directly from data (reports, statistics, etc.). Moreover, providing feedback divulges completely new, hidden, and interesting information found in data [32].

There are studies regarding these features such as: to identify interesting and unexpected learning patterns, which in turn may provide decision lines, enabling teachers to more efficiently organize their teaching structure [33]; to provide feedback to the course instructor about how to improve courseware [25]; to analyze the user's access log in improve e-e-learning and to support the analysis of trends [1]; to help the teacher to discover beneficial or detrimental relationships between the use of web-based educational resources and student's learning [6]; to reveal information about university students' enrolment [28]; learning decomposition and logistic regression to compare the impact of different educational interventions on learning [3]; and usage data analysis to improve the effectiveness of the learning process in e-learning systems [19].

The role of educational content in learning is crucial. The key factor to success is high quality educational content, appropriate for learning and able to fulfil course educational aims and objectives [16]. Most of the times it is not an easy task to give feedback to instructors about the online educational content [32]. However, some course characteristics and students' actions may reflect the quality and quantity of the educational content [29].

This study analyzes the effects of blended learning in an institute and its students. The approach goes backward to examine whether this courses usage by the learners is strongly affected by the educational content exposed by the instructors. It proposes the variables Richness and Usefulness, taking into account statistics concerning the courses. These variables aim to help course instructors and/or platform administrators review course usage and find course weaknesses.

2. Research Method

In order to ascertain the views of students about blended learning in TEI of WM, a self administrative questionnaire was chosen to collect the data. Students study the courses for 12 weeks. At the end of the 12th week they were asked to evaluate the three courses they had studied by filling in, an online questionnaire for each course they had studied. The experimental measurements took place at the first semester of 2016 and the qualitative data were gathered.

In the questionnaire we chose closed questions for quick completing and data processing. Moreover, the questions were multiple choice, where it is possible to choose among several predefined answers and most of them were questions of scale or preference, where the degree of preference of the respondent stated. They are the most important questions in a questionnaire, because they allow classification of the views or attitudes of respondents.

The chosen scales in this research are the Likert and the Gutman. In Likert scale, the attitudes have five response categories "Totally agree" = 5, "Agree" = 4, " Neither agree nor disagree" = 3, "Disagree" = 2, "Totally disagree" = 1. In the Gutman scale the attitudes have two response categories "Yes" and "No".

Furthermore we attended the questionnaire marked by clearness and clarity. The questions were short and clear. The negative questions were avoided because they are often misunderstood, since the negative keyword is ignored and the respondent gives an answer that is contrary to his real opinion. Also we did not include questions with double meaning, because they require the respondent to answer two separate ideas with a single answer.

The questionnaire consists of 22 questions and is divided in four parts. The first part consists of 5 questions and examines the students' personal profile. Knowledge of the students profile is important, in order to understand the needs and the personal characteristics of the learners. The second part has 1 question concerning the

	Edu Type	N	Mean	Std. Deviation	Std. Error Mean
Rich Content	1.00	69	3.6087	.91100	.10967
	2.00	69	3.4348	.86566	.10421
Useful Content	1.00	69	3.6522	.88826	.10693
	2.00	69	3.3333	.90207	.10860

Table 1: Group Statistics for Edutype. Edutype 1: Traditional learning, Edutype 2: Electronic learning.

blended learning. The third part consists of 7 questions and deals with the attitudes of respondents in relation to traditional learning. The fourth part consists of 9 questions concerning the attitudes of respondents in relation to e-learning. Eight questions are about richness of the course and nine questions are about usefulness of the course in both education types (traditional and e-learning).

The questionnaire was completed by sixty nine (69) learners. All statistical analysis was conducted with the application of the SPSS version 19 software package. The deterministic variables are the questions of our questionnaire. After a thorough analysis, the questionnaire responses show us if the deterministic variables are suitable to measure the hidden variables (richness and usefulness) and how they affect the formation of the students' intention in the adoption and use of blended learning. The analysis is focused on the two hidden variables, each determined by the deterministic variables.

We will investigate possible correlations between specific course properties. Specifically:

1. We compare the educational content in both education types traditional and electronic learning.
2. We correlate gender and with richness and usefulness.
3. We compare courses in terms of richness.
4. We compare courses in terms of usefulness.
5. We discover thoroughly the differences among the courses.

3. Results

The variables rich Content and Useful Content are the hidden variables of the questionnaire. Their values are derived from the deterministic variables which are the questions of our questionnaire. The richness is translated into rich Content and usefulness is translated into Useful Content according to the meaning of the questions.

3.1. Comparison of the Educational Contents between Traditional and Electronic Learning for the 3 Courses

The content in traditional education (edutype=1) is more useful with a significant statistical difference. Also, they felt slightly richer (no statistically significant difference).

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Differen	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Lower
Rich Content	Equal variances assumed	.000	.987	1.150	136	.252	.17391	.15129	-.12527	.47309
	Equal variances assumed			1.150	135.647	.252	.17391	.15129	-.12528	.47310
Useful Content	Equal variances assumed	.057	.811	2.092	136	.038	.31884	.15241	.01745	.62024
	Equal variances assumed			2.092	135.968	.038	.31884	.15241	.01745	.62024

Table 2: Independent Samples Test.

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Rich Content	1.00	84	3.6548	.85720	.09353
	2.00	54	3.3148	.90750	.12349
Useful Content	1.00	84	3.6310	.95413	.10410
	2.00	54	3.2778	.78708	.10711

Table 3: Group Statistics for Gender. Gender 1: Men, Gender 2: Women.

This means that they prefer to reuse content from traditional education for their course. The instructors should improve quality the supplied content via Internet.

3.2. Correlation between Gender with Richness and Usefulness

There is a difference between women and men. The men (gender = 1) find the content more useful (mean 3.63) than women (mean 3.2778) and there is a statistically significant difference. Despite the fact that men perceive it slightly richer, there is a statistically significant difference. This leads to the conclusion that men can exploit this content and learn better from it. However, women have difficulties in understanding; this justifies they do not rate it, as useful as men. However, it is quite a good content since the rating is above 3. Therefore, the instructors should make it more understandable to women, perhaps with more and better examples.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	86	3.5698	.81948	.08837	-.12527	2.00	5.00	
2.00	22	2.9545	1.04550	.22290	-.12528	1.00	5.00	
3.00	30	3.8000	.80516	.14700	.01745	2.00	5.00	
Total	138	3.5217	.88966	.07573	.01745	1.00	5.00	

Table 4: Descriptives for Rich Content.

Levene Statistic	df1	df2	Sig.
.790	2	135	.456

Table 5: Test of Homogeneity of Variances.

3.3. Comparison of Courses in Terms of Richness

We have the overall course evaluation in both traditional and electronic and the comparison among the courses about the richness of the educational content. In table 4, we have the descriptive statistics for the results

For a valid measurement, the criterion Levene Statistic has to be not significant, namely to have equal variances.

From the above table 5, the value is 0.456, so our measure is valid. We can see in the following results, if there is a statistically significant difference among the courses. Through the next table 6, we see that there is a statistically significant difference with p=0.002<0.05 among some courses (even do not know yet which courses).

Moving towards post hoctests, we see through the table 7 below in which courses there is significant statistical difference about the richness of their content

From the above table 7 we see that the first course is better than the second course (difference score by 0.615 in the answers) with statistically significant difference (p=0.009). The second course is also worse than the third course (worse score at 0.84545 units) with a statistically significant difference of 0.002. The courses 1 and 3 have no significant statistical difference between them. This means that in second course, it is necessary to add new content.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9.599	2	4.799	6.556	.002
Within Groups	98.836	135	.732		
Total	108.435	137			

Table 6: ANOVA Rich Content.

(I) Courses	(J) Courses	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	.61522*	.20443	.009	.1308	1.0997
	3.00	-.23023	.18143	.415	-.6602	.1997
2.00	1.00	-.61522*	.20443	.009	-1.0997	-.1308
	3.00	-.84545*	.24017	.002	-1.4146	-.2763
3.00	1.00	.23023	.18143	.415	-.1997	.6602
	2.00	.84545*	.24017	.002	.2763	1.4146

Table 7: Multiple Comparisons with the dependent variable RichContent (TukeyHSD). * The mean difference is significant at the 0.05 level.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	86	3.5814	.92628	.09988	3.3828	3.7800	1.00	5.00
2.00	22	3.3182	1.04135	.22202	2.8565	3.7799	1.00	5.00
3.00	30	3.3667	.71840	.13116	3.0984	3.6349	2.00	5.00
Total	138	3.4928	.90615	.07714	3.3402	3.6453	1.00	5.00

Table 8: Descriptives for Rich Content.

3.4. Comparison of Courses in Terms of Usefulness

In the same test for the usefulness of the content, we do not observe significant statistical changes. In the table 8, we have the mean values.

For a valid measurement, the criterion Levene Statistic has to be not significant, namely to have equal variances. From the table 9 below, the value is 0.143, so our measure is valid. We can see in the following results, if there is a statistically significant difference among the courses. Through the next table, we see that there is not a statistically significant difference with $p = 0.332 > 0.05$ among some courses. So, it is not necessary to analyze thoroughly the particular courses.

3.5. Thorough Analysis for the Differences among the Courses

We apply ANOVA for all the variables and we have the following descriptive statistics.

The Levene Statistic (table 13) indicates a problem for traditional Rich Content, since it is statistically significantly differentiated the variation of the sample (with

Levene Statistic	df1	df2	Sig.
1.977	2	135	.143

Table 9: Test of Homogeneity of Variances.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.823	2	.912	1.112	.332
Within Groups	110.670	135	.820		
Total	112.493	137			

Table 10: ANOVA for Useful Content.

(I) Courses	(J) Courses	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	.26321	.21632	.445	-.2494	.7759
	3.00	.21473	.19198	.504	-.2402	.6697
2.00	1.00	-.26321	.21632	.445	-.7759	.2494
	3.00	-.04848	.25414	.980	-.6508	.5538
3.00	1.00	-.21473	.19198	.504	-.6697	.2402
	2.00	.04848	.25414	.980	-.5538	.6508

Table 11: Multiple Comparisons with the dependent variable Useful Content (TukeyHSD).

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
t Rich Content	1.00	43	3.6744	.80832	.12327	3.4257	3.9232	2.00	5.00
	2.00	11	3.1818	1.32802	.40041	2.2896	4.0740	1.00	5.00
	3.00	15	3.7333	.79881	.20625	3.2910	4.1757	2.00	5.00
	Total	69	3.6087	.91100	.10967	3.3898	3.8275	1.00	5.00
t Useful Content	1.00	43	3.6977	.93948	.14327	3.4085	3.9868	1.00	5.00
	2.00	11	3.8182	.87386	.26348	3.2311	4.4053	2.00	5.00
	3.00	15	3.4000	.73679	.19024	2.9920	3.8080	2.00	5.00
	Total	69	3.6522	.88826	.10693	3.4388	3.8656	1.00	5.00
e Rich Content	1.00	43	3.4651	.82661	.12606	3.2107	3.7195	2.00	5.00
	2.00	11	2.7273	.64667	.19498	2.2928	3.1617	2.00	4.00
	3.00	15	3.8667	.83381	.21529	3.4049	4.3284	2.00	5.00
	Total	69	3.4348	.86566	.10421	3.2268	3.6427	2.00	5.00
e Useful Content	1.00	43	3.4651	.90892	.13861	3.1854	3.7448	1.00	5.00
	2.00	11	2.8182	.98165	.29598	2.1587	3.4777	1.00	4.00
	3.00	15	3.3333	.72375	.18687	2.9325	3.7341	2.00	5.00
	Total	69	3.3333	.90207	.10860	3.1166	3.5500	1.00	5.00

Table 12: Descriptives for all the variables.

	Levene Statistic	df1	df2	Sig.
t Rich Content	4.014	2	66	.023
t Useful Content	.363	2	66	.697
e Rich Content	.971	2	66	.384
e Useful Content	.866	2	66	.425

Table 13: Test of Homogeneity of Variances.

		Sum of Squares	df	Mean Square	F	Sig.
t Rich Content	Between Groups	2.423	2	1.212	1.481	.235
	Within Groups	54.012	66	.818		
	Total	56.435	68			
t Useful Content	Between Groups	1.346	2	.673	.849	.432
	Within Groups	52.306	66	.793		
	Total	53.652	68			
e Rich Content	Between Groups	8.344	2	4.172	6.461	.003
	Within Groups	42.613	66	.646		
	Total	50.957	68			
e Useful Content	Between Groups	3.666	2	1.833	2.341	.104
	Within Groups	51.667	66	.783		
	Total	55.333	68			

Table 14: ANOVA.

p=0.023<0.05); in this case we should use, instead of ANOVA, the Kruskal-Wallis H test for the analysis of traditional Rich Content.

In the table 14, we see the significant statistical difference only for variable e Rich Content (with p=0.003<0.005) between courses.

Table 15 shows that the courses 1 and 3 are significantly better than the course 2. Especially, for the first course we have p=0.023; it has better rating at 0.73784 units than second course and third course with p=0.002 is better at 1.13939 units than second course. So, instructors need to add more content in the second course. We also test the traditional Rich content among the courses with Kruskal-WallisTest since Levene test was significant differentiated at the ANOVA test. The statistics per course are shown at Table 15.

The table 16 shows that there is no significant statistical difference between courses since p=0.447>0.05. So, it is not necessary to add more content.

Dependent Variable	(I) Courses	(J) Courses	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
e Rich Content	1.00	2.00	.73784*	.27150	.023	.0869	1.3888
		3.00	-.40155	.24095	.226	-.9793	.1762
	2.00	1.00	-.73784*	.27150	.023	-1.3888	-.0869
		3.00	-1.13939*	.31896	.002	-1.9042	-.3746
	3.00	1.00	.40155	.24095	.226	-.1762	.9793
		2.00	1.13939*	.31896	.002	.3746	1.9042

Table 15: Multiple Comparisons, Dependent Variable: Rich Content –Tukey HSD. * The mean difference is significant at the 0.05 level.

	Course	N	Mean Rank
t Rich Content	1.00	43	35.94
	2.00	11	28.55
	3.00	15	37.03
	Total	69	

Table 16: Ranks of the traditional Rich content.

4. Discussion and Conclusions

This study evaluates the use of blended learning in TEI of West Macedonia with the use of structured questionnaires exposed to the learners. The learners express their attitude about how useful the blended learning is and how this blended means facilitates their studies. It proposes two variables Richness and Usefulness, taking into account statistics concerning the courses. These variables aim to help course instructors and administrators review course usage and find course weaknesses.

There are assessed both traditional and e-learning. There were assessed taking into account the gender of the respondents for the three courses.

From the overall comparison of the educational contents between traditional and electronic learning for the 3 courses, it is discovered that the content in traditional learning (edutype=1) is more useful with a significant statistical difference. They think that it is slightly richer than e-learning. This means that they prefer to reuse content

	t Rich Content
Chi-Square	1.610
df	2
Asymp. Sig.	.447

Table 17: Kruskal-Wallis Test Statistics[a,b]. a Kruskal-Wallis Test, b Grouping Variable: Course.

from traditional learning for their course. The instructors should improve quality the supplied content in e-learning.

Significant differences were found between the attitudes of women and men. The men find the content more useful than women with a significant statistically difference. This leads to the conclusion that men can exploit this content and learn better from it. Maybe, women have difficulties in understanding; this justifies they do not rate it, as useful as men. However, it is quite a good content since the rating is above 3. Therefore, the instructors should make it more understandable to women, perhaps with more and better examples.

From the results regarding richness, we conclude that the first course is better than the second course. The third course is also better than the second course with a statistically significant difference. The courses 1 and 3 have no significant statistical difference between them. This means that in second course, it is necessary to add new content.

From the results regarding richness, we conclude that the first course is better than the second course. The third course is also better than the second course with a statistically significant difference. The courses 1 and 3 have no significant statistical difference between them. This means that in second course, it is necessary to add new content. In contrast, from the results regarding usefulness, there were not discovered statistically significant differences among the courses.

From the thorough analysis of the courses, we conclude that the first and third courses are significantly better than the second course. So, the instructors need to add more content in the second course.

The research of this study in no way could be considered full, since the sample of respondents is small, in one only institute and for three only courses. Enlargement and reopening of the investigation in future will pay more accurately the views of learners in order to provide safer conclusions. The sample of respondents will consist of many different institutes. There will be a second questionnaire for educators/facilitators/administrators for a twofold evaluation. A causal model will be adopted which will explain the factors which affect the usage of blended learning. A confirmatory factor analysis will be performed in the model.

References

[1] C. B. Baruque, M. A. Amaral, A. Barcellos, J. C. Da Silva Freitas, and C. J. Longo, Analysing users' access logs in Moodle to improve e learning, in Proc. Euro Amer. Conf. Telematics Inf. Syst., Faro, Portugal, pp. 1–4.

[2] M. Feng and N. Heffernan, Informing teachers live about student learning: Reporting in the assistment system, *Technol., Instruction, Cognition, Learn. J*, **3**, p. 1, (2006).

[3] M. Feng, J. E. Beck, and N. T. Heffernan, Using learning decomposition and bootstrapping with randomization to compare the impact of different educational interventions on learning, 51–60.

[4] D. Fichter, Intranet librarian: Intranets and ELearning: A perfect partnership, *Online (Wilton, Connecticut)*, **26**, no. 1, p. 68, (2002).

[5] R. Babo and A. Azevedo, General perspective in learning management systems, *Higher Education Institutions and Learning Management Systems: Adoption and Standardization*, 1–374, (2011).

[6] E. García, C. Romero, S. Ventura, and C. D. Castro, An architecture for making recommendations to courseware authors using association rule mining and collaborative filtering, *User Modeling and User-Adapted Interaction*, **19**, no. 1-2, 99–132, (2009).

[7] D. R. Garrison and N. Vaughan, *Blended learning in higher education*, Jossey-Bass, San Francisco, 2007.

[8] J. A. Garrison, C. Schardt, and J. K. Kochi, Web-based distance continuing education: A new way of thinking for students and instructors, *Bulletin of the Medical Library Association*, **88**, no. 3, 211–217, (2000).

[9] J. Gibbs and M. Rice, Evaluating student behavior on instructional Web sites using web server logs, p. 1.

[10] H. L. Grob, F. Bensberg, and F. Kaderali, Controlling open source intermediaries - A web log mining approach, 233–242.

[11] H. Jin, T. Wu, Z. Liu, and J. Yan, Application of visual data mining in higher-education evaluation system, 101–104.

[12] N. Hara and R. Kling, Students’ frustrations with a web-based distance education course, *First Monday*, **4**, no. 12, (1999).

[13] G.-J. Hwang, P.-S. Tsai, C.-C. Tsai, and J. C. R. Tseng, A novel approach for assisting teachers in analyzing student web-searching behaviors, *Computers and Education*, **51**, no. 2, 926–938, (2008).

[14] A. Ingram, Using web server logs in evaluating instructional web sites, *J. Educ. Technol. Syst*, **28**, no. 2, 137–157, (2003).

[15] I. Kazanidis, T. Theodosiou, I. Petasakis, and S. Valsamidis, *Online courses assessment through measuring and archetyping of usage data, Interactive Leaning Environments*, http://www.tandfonline.com/doi/abs/10.1080/10494820.2014.

[16] I. Kazanidis, S. Valsamidis, S. Kontogiannis, and A. Karakos, B , Courseware Evaluation Through Content, Usage and Marking Assessment, in *in Research on e-Learning and ICT in Education Technological, Pedagogical and Instructional Perspectives : Charalampos Karagiannidis, Panagiotis Politis, Ilias Karasavvidis, ISBN*, (Online), Eds., 4614–6500, http, //dx.doi.org/10.1007/978-1-4614-6501-0, 2013.

[17] R. Mazza, *Introduction to Information Visualization*, Springer-Verlag, New York, 2009.

[18] D. Monk, Using data mining for e-learning decision making, *Electron. J. E-Learning*, **3**, no. 1, 41–54, (2005).

[19] P. B. Myszkowski, H. Kwaśnicka, and U. Markowska-Kaczmar, Data mining techniques in e-learning CelGrid system, 315–319

[20] R. N. Olafsen and D. Cetindamar, E-learning in a competitive firm setting, *Innovations in Education and Teaching International*, **42**, no. 4, 325–335, (2005).

[21] C. Pahl and C. Donnellan, Data mining technology for the evaluation of web-based teaching and learning systems, in, in *Proc. Congr. E-Learning*, p. 1, Canada, Montreal, 2003.

[22] W. W. Porter and C. R. Graham, Institutional drivers and barriers to faculty adoption of blended learning in higher education, *British Journal of Educational Technology*, **47**, no. 4, 748–762, (2016).

[23] J. Reay, Blended learning - a fusion for the future, *Knowledge Management Review*, **4**, no. 3, p. 6, (2001).

[24] C. Romero, P. González, S. Ventura, M. J. del Jesus, and F. Herrera, Evolutionary algorithms for subgroup discovery in e-learning: A practical application using Moodle data, *Expert Systems with Applications*, **36**, no. 2, 1632–1644, (2009).

[25] C. Romero, S. Ventura, and P. De Bra, Knowledge discovery with genetic programming for providing feedback to courseware authors, *User Modelling and User-Adapted Interaction*, **14**, no. 5, 425–464, (2004).

[26] J. E. Rooney, Blending learning opportunities to enhance educational programming and meetings, *Association Management*, **55**, no. 5, 26–32, (2003).

[27] P. Sands, Inside outside, upside downside: Strategies for connecting online and face-to-face instruction in hybrid courses, in *Teaching with Technology Today*, **8**, upside downside, Strategies for connecting online and face-to-face instruction in hybrid courses. Teaching with Technology Today, 2002.

[28] A. P. Sanjeev and J. M. Zytkow, Discovering enrolment knowledge in university databases, 246–251

[29] T. Theodosiou, I. Kazanidis, S. Valsamidis, and S. Kontogiannis, Courseware usage archetyping, 243–249.

[30] M. Ueno, Data mining and text mining technologies for collaborative learning in an ILMS "Samurai", 1052–1053.

[31] I. Kazanidis, S. Valsamidis, S. Kontogiannis, and A. Karakos, Measuring and mining LMS data, 296–301.

[32] S. Valsamidis, S. Kontogiannis, I. Kazanidis, and A. Karakos, 2012B, An approach for LMS assessment, **35**, 265–283, http://inderscience.metapress.com/content/a26wq71n727973k0/.

[33] Wang, F. H., 2002, On using data-mining technology for browsing log file analysis in asynchronous learning environment, in Proc. World Conf. Educ. Multimedia, Hypermedia Telecommun., Chesapeake, VA, pp. 2005–2006.

[34] J. Ward and G. A. La Branche, *Blended learning: The convergence of e-learning and meetings. Franchising World*, **35**, Blended learning, The convergence of e-learning and meetings. Franchising World, 2003.

[35] A. K. W. Wu and C. H. Leung, Evaluating learning behavior of Web-Based Training (WBT) using Web log, 736–737.

[36] J. R. Young, Hybrid' teaching seeks to end the divide between traditional and online instruction, *Chronicle of Higher Education*, **48**, no. 28, A33–A34, (2002).

[37] C. Zinn and O. Scheuer, Getting to know your student in distance learning contexts, *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, **4227**, 437–451, (2006).

[38] M. E. Zorrilla, E. Menasalvas, D. Marín, E. Mora, and J. Segovia, Web usage mining project for improving Web-based learning sites, *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, **3643**, 205–210, (2005).

[39] L. Zoubek and M. Burda, Visualization of differences in data measuring mathematical skills, 315–324.