ISSN 2278-3091
Volume 8, No.6, November – December 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse113862019.pdf
https://doi.org/10.30534/ijatcse/2019/113862019

Analysis of Students Online Learning Behavior in a Pedagogical Model combining Blended Learning and Competency Based Approach

Sami Hachmoud[1], Adil Hachmoud[2], Anwar Meddaoui[3], Hakim Allali[4]
[1]University of Hassan I, FST Settat, Morocco, sami.hachmoud@gmail.com
[2]University of Sidi Mohamed Ben Abdellah, EST Fès, Morocco, adil.hachmoud@usmba.ac.ma
[3]University of Hassan II. ENSAM Casablanca, Morocco, ameddaoui@gmail.com
[4]University of Hassan I, FST, Department of Applied Mathematics and Computer Science, Morocco, hakim-allali@hotmail.fr

ABSTRACT

The purpose of this paper is to analyze students' learning behavior through a Learning Management System using a compound model of Blended Learning and Competency-Based Approach. The article investigates correlations between students' activities in online environment and competencies acquisition in classroom. The analysis was performed using activities log obtained from various cognitive resources provided online using Moodle platform. This work has shown that log data exploration and analysis can be used to generate visualizations about students' learning behavior. The current study can help teachers monitor students' engagement level and make upstream decisions about competency development. Further researches could use presented findings to implement other case studies using the same pedagogical model.

Key words: Blended Learning; Competency Based Approach; Moodle; Learning Management System.

1. INTRODUCTION

Students are the key entity to consider in all learning models; close monitoring of students is therefore an essential element for quality learning, since it provides both the means for personalized feedback and support as well as for the improvement of the program. This monitoring can be ensured through student performance analysis using log files. This data could help teachers make informed decisions about potential problems and find appropriate ways to effectively resolve them. We can use multiple data mining methods to examine data from a Learning Management System [1]. Baker and Yacef [2] recognized that data mining was a promising area for the exploration of data from learning systems.

Various studies, using log files, have been conducted to analyze learners' online behaviors and predict their future achievements. In recent years, various approaches have been applied to identify various technology-assisted learning problems. Romero [3] noted a trend towards the use of data mining techniques for analyzing activity data. New disciplines such as Educational Data Mining (EDM) and (LA) Learning Analytics focus on development of methods for exploring and analyzing data from educational fields [4], [5],[6].

Data mining techniques have been applied to several online learning problems, such as: classifying students according to their learning performance; online navigation system; detection of irregular learning behaviors; grouping according to similar use of e-learning system and the adaptability of the systems to the students' needs [7].

Rokach and Maimon [8] have divided data mining techniques for educational data into two groups: discovery-oriented techniques based on prediction and description and verification-oriented techniques based on traditional statistics such as ANOVA that will be addressed in this study.

A brief overview is presented in the next section on research work carried out in this context

2. RELATED WORK

2.1 The use of data mining for the analysis of LMS data

Romero, Ventura, and García [9] describe the process of extracting e-learning data, as the instructions for using data mining techniques to extract Moodle data. Kazanidis [10] proposed a framework for data processing and analysis of LMS.

2.2 Activity logs' correlation with final marks

Luik and Mikk [11] deduced a non-linear relationship between connections and students' performance based on cluster results. Mogus, Djurdjevic, and Suvak [12] determine whether student activity logs correlate with their final grades. Assignment view, course view, forum view and resource view, were the main activities influencing students' grades. The authors concluded that these four activities particularly influence the effectiveness of learning. Pislaru and Mishra [13] found a correlation between components of the LMS and the final students' grades. Champaign [14] identify patterns in student behavior; there is a strong negative correlation between student's skills and the time spent doing online tasks. Wen and Rosé [15] analyzed students' behavior in individual sessions using the 'Clickstream' data of MOOC courses; students divide their activities differently according to their grades and course performance level. Gašević [16] conducted a statistical analysis that included an analysis of variance (ANOVA), a chi-square test, and a linear regression to explore the association between students 'online interactions and students' scores.

2.3 Prediction of student's performance

Cocea and Weibelzahl [17] analyzed 10 attributes to identify engagement (an aspect of motivation) as a key factor in quality of learning. Jovanovic [18] defined a classification model to predict whether a student would achieve excellent performance in a course. They defined cluster models that would detect clustering of students with respect to their overall performance and used a k-means clustering algorithm for categorical data. Kotsiantis [19] used regression techniques to predict student scores in a distance learning system. Stored data (virtual courses and online learning log file) have been useful for predicting grades. Kotsiantis [20] studied ten different variables related to student activities.

2.4 Students' clustering (grouping profile)

Jovanovica [18] applied classification models for predicting student performance and cluster models to group students according to their cognitive styles in an e-learning environment. Agnihotri [21] studied in depth the data generated when interacting with a tool called «Connect» to group the students. Their results identified three distinct groups of students: « highest performers », « lowest performers » and « persistent students ». Bovo [22] studied Moodle logs to group the students. They aim to define the relevant clustering features.

These studies are a source of motivation for our research work insofar as it provokes our curiosity to analyze data resulting from such a pedagogical model little explored in previous studies.

3. PEDAGOGICAL MODEL AND RESEARCH DESCRIPTION

Adoption of Competency Based Approach is becoming a necessity for several reasons: « The labor market needs and the economic changes», « demands for occupational performance in contemporary workplaces» and « it's a new concept for communication with employers » [23]. In the context of this study, learners come from the occupational world and present different cognitive profiles and consequently different knowledge needs. The use of a blended learning mode seems to be the most appropriate way for them to personalize their learning pathways (spend more time on things they do not know and go faster through things already seen). Blended and online learning platforms allow to customize instruction to meet the knowledge of each student [24].

Associating Competency Based Approach (CBA) with Blended Learning (BL) will therefore allow learners to devote the whole time of face-to-face to knowledge mobilization and integration. Proposed pedagogical model aims to develop students' competencies through the resolution of Learning and Evaluation Situations (LES). The first situations are proposed to the student in order to teach him how to cope with complexity, the following situations are proposed as part of a formative assessment, where his difficulties are detected. These situations, called «target situations» [25], are defined in relation to the basic competencies to acquire. Student certification is also based on student's success in concrete and complex situations, and not on restitution of knowledge or simple application of learned techniques.

Implemented process begins with a LES proposition. In order to propose an adapted LES, teachers could use the portfolio describing learner profile and its progress on curriculum [26]. Thus, if the portfolio evokes shortcomings on a particular aspect of a specific competency, teacher could propose a LES focusing on this particular aspect, he identifies necessary resources to process the LES and input appropriate resources to both the LES and the student profile into the LMS. The student begins learning by studying the situation, then proceeds to acquire the resources provided on the LMS, requests or proposes additional resources. If resources require special learning, students could use those resources in usual learning context [27]. Teachers will be able to provide additional resources, to guide the learner or to identify assessment indicators. In assessment phase, teachers have to decide on the next step according to learner's performance, if proposed solutions are not complete, learners are requested to propose improvement by providing other resources or by offering another less complex LES. If solutions are satisfactory, concerned teacher possibly will decide to move to more complex LES. This process could be repeated until the pedagogical team decides to end it. The professor could then confirm student’s achievements and update their profile to certify the competence developed. Figure 1.

Teachers are expected to be able to intervene at any time either to provide additional or more appropriate resources or to guide student. Except this context, resources are consulted online and teachers have no feedback about their use.

This study aims to provide feedback about the use of LMS resources by students, for this purpose, as a first step, the study explores possible relationship between the observed variables and the student level of competency. Secondly, it examines activity logs in order to detect frequency of use and to find trends in student behavior. The purpose is to determine the impact of LMS usage behavior on competency development. Therefore, the study should provide answers to the following research questions:

1. To what extent are students' level of competency related to their LMS activities, namely Moodle, who mediated a blended learning course using competency-based approach?
2. Is there a correlation between LMS activities and student level of competency?
3. Could the knowledge gained during this exploration of logs provide a feedback on learning process to teachers?

To answer these research questions, a Moodle log file was collected after the completion of a blended learning module

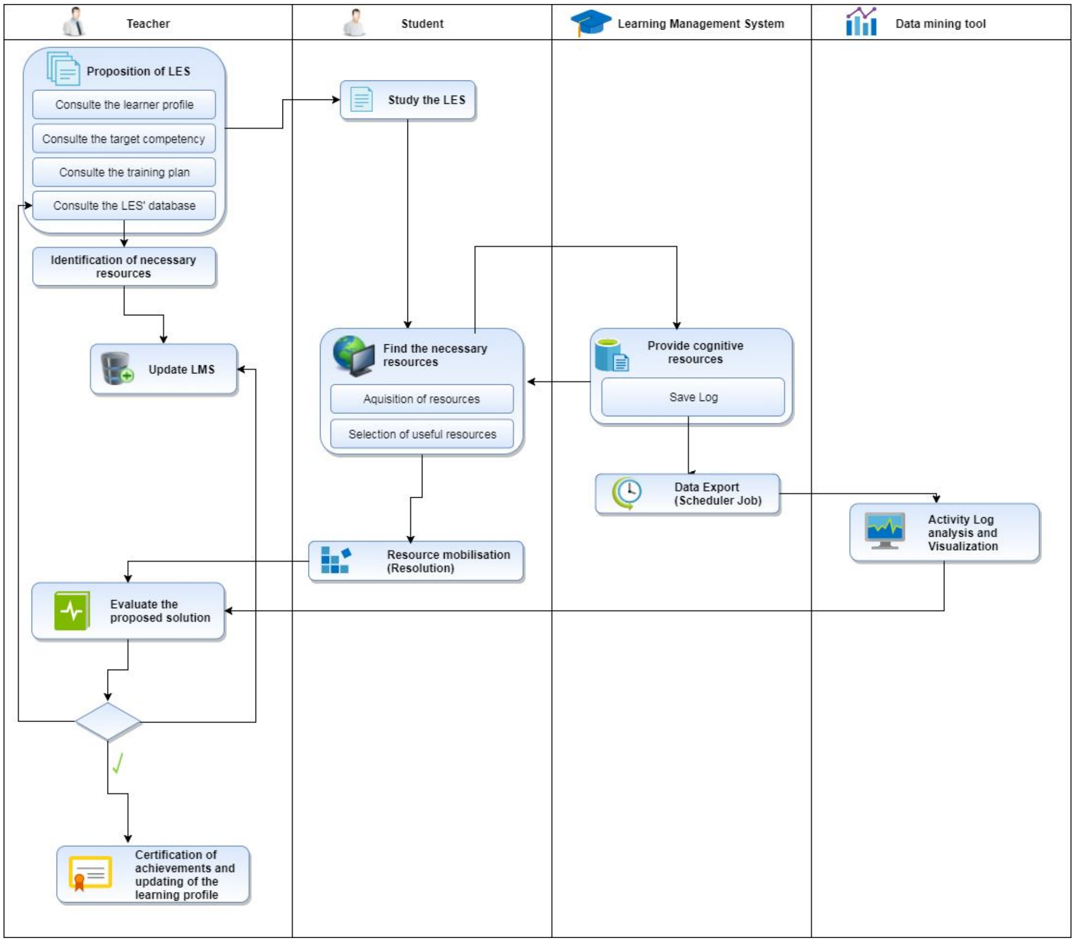

Figure 1: Process Model Combining Blended Learning and Competency-Based Approach

using competency-based approach as a pedagogical model, entitled "Management of industrial maintenance". A total of 59 students enrolled in Moodle, weekly 240-minute face-to-face classes were held in one semester. Moodle log consists of the time and date it was accessed, the IP address from which it was accessed, the student name, action performed (display, adding, updating or deleting), activities in different modules (forum, resources or assignment sections). Stored data can be useful for data mining algorithms [28].

4. STUDY CASE

4.1 Data collection

The procedure used for data collection and analysis included 4 phases [9]:

a) Data collection;

b) Preliminary data processing using appropriate algorithms for research questions;

c) Application of data analysis methods

d) Interpretation of results and conclusions.

A considerable number of interaction logs were extracted from Moodle for this purpose, combined with the gender of each student and the final grade assigned to each student based on their level of competency development (Acquired (A), In progress (B), No acquired (C). The data collection process was performed using "Moodle logs plugin" by generating Comma-Separated Values (CSV file). Each event record in log has six attributes: course name, event date and time, IP address, username, action and information.

Data in CVS format has been stored in a relational database. Subsequently, appropriate Structured Query Language (SQL queries) were applied to identify the following variables for each student: log-in frequency, total log-in time, total number of resources accessed. Finally, the pre-processed data obtained was imported on a free Data Mining software (Orange) to allow various analysis and visualizations.

4.2 Data analysis and results

All types of data captured by Moodle were used to explore correlation of each attribute with student's competency level. The grade indicates the level of competency acquisition (category A if competency is "Acquired", category B if competency acquisition is "In progress" and category C if competency is "Not acquired").

Figure 2 shows the distribution of number of connections by student competency level, the highest average number of connections is obtained by students with the highest competency level (category A). The Figure 3 also shows the relative connection frequency for each competency level, the highest density corresponds to the highest competency level.

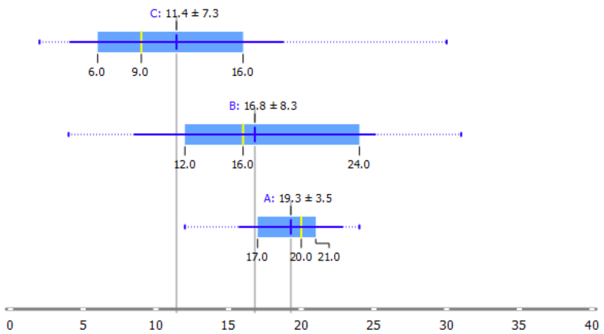

Figure 2: Distribution of log-in frequency by Competency level (with compare means) ANOVA: 4.961 (p=0.010)

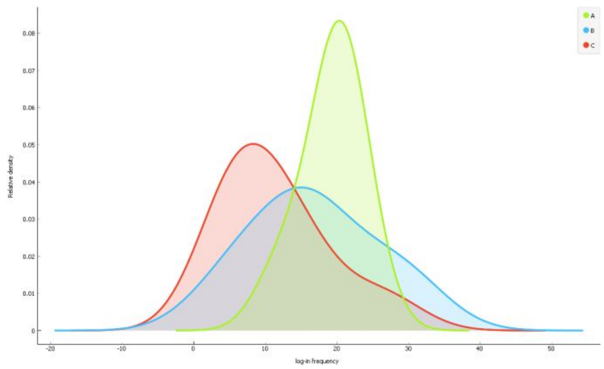

Figure 3: Relative log-in frequency grouped by Competency level

To determine if there is a correlation between specific attributes of the LMS and students' level, we performed a correlation analysis Table 1. For data analysis purposes, a numerical value is assigned to each competency level.

Table 1: Correlation between variables (Pearson distance metric)

	Log-in frequency	Resources viewed	Time log-in	Grade
Log-in frequency	0.000	0.067	0.124	0.467
Resources viewed	0.067	0.000	0.101	0.463
Time log-in	0.124	0.101	0.000	0.466
Grade	0.467	0.463	0.466	0.000

Table 1 examines correlations between results obtained and the number of connections, the total connection time (in minutes) and the quantity of resources visualized. The results indicate a statistically significant correlation between grades (level of competency) and other attributes of students. The correlation is positive, indicating that students with a higher number of connections have higher level of competency. There is no association between the number of connections and the number of resources viewed.

An analysis of students' activities by gender was also carried out Figure 4. Male students consulted more resources than their female colleagues. Differences between genders were also identified in the average score received in Figure 5. Female students have a higher average score than male students. They also have a slightly higher average number of connections than male students Figure 6.

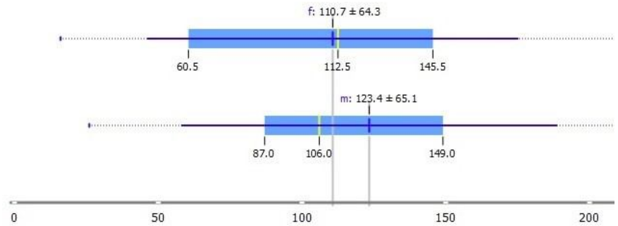

Figure 4: Distribution of resources viewed by gender [Student's t: 0.702 (p=0.487) with compare means]

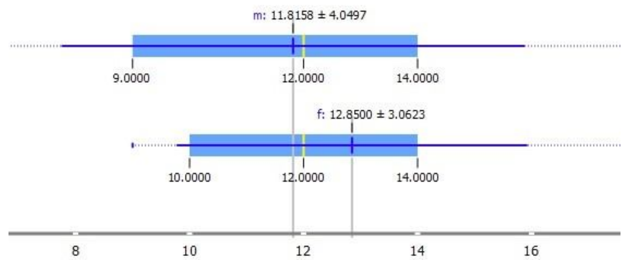

Figure 5: Grade distribution by gender [Student's t:0. 987 (p=0.332) with compare means]

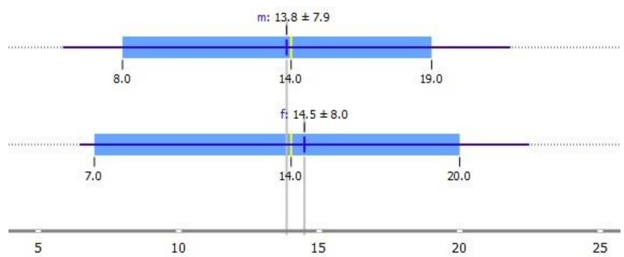

Figure 6: Distribution of log-in frequency by Gender [Student's t: 0. 286 (p=0.777) with compare means]

The idea of the next analysis is to determine the distribution of student activities around assessment dates. The purpose of assessment is to attest students' knowledge integration through Learning and Evaluation Situations.

The analysis carried out concerns' student activities from the 1st to the 12th week of the course, the first assessment took place on 02 March 2018 (the 5th week of learning) and the second took place on 03 May 2018 (the 12th week of the course). Visualization of activities over the time. Figure 7 shows that the highest number of connections appears in the days preceding the assessment days. The types of activities more consulted are: Lesson activity, Courses file and Tests.

For greater clarity about this behavior and its relation to the student competency level; the student activities represented over the time have been grouped with respect to the students' competency level Figure 7.

The visualization shows that students with good or medium competency levels (Category A and B in Blue and Red) consult the LMS on a regular basis, while students with a lower level of competency (Category C in green) consult the LMS only during the assessment periods.

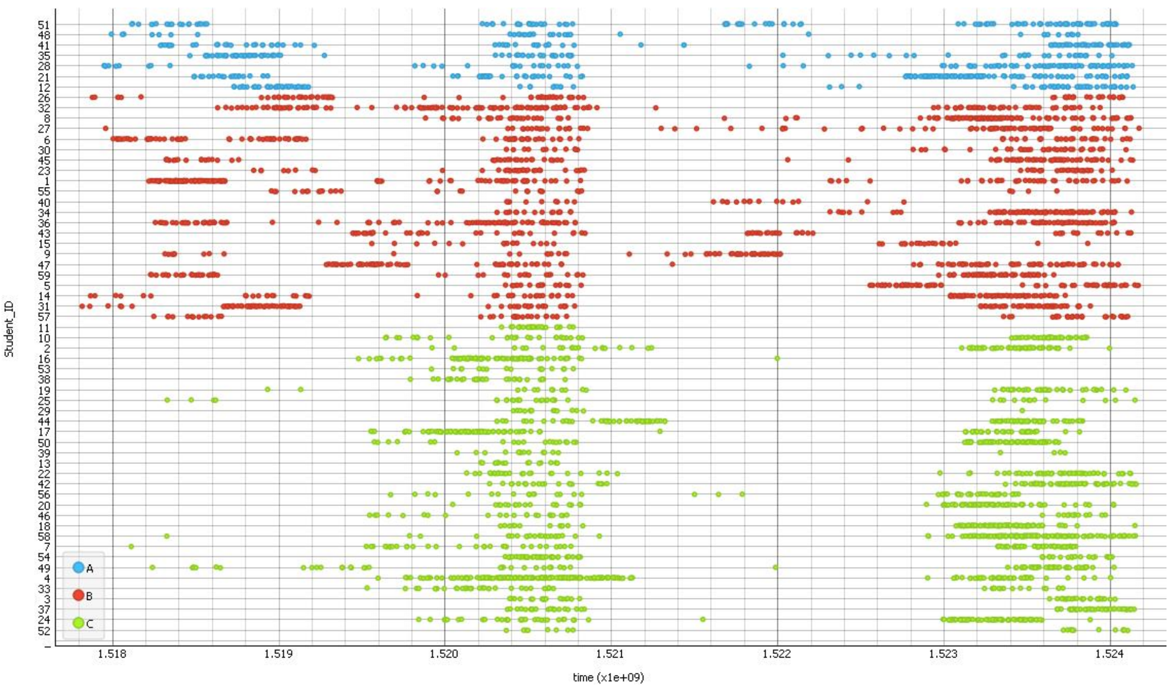

Figure 7: Connection regularity: Interaction over time grouped by Competency level

5. DISCUSSION

In this study, both male and female students who accessed to the LMS on a regular basis had satisfactory results, female students were slightly more active and successful in this course compared to male students. There is a correlation between the number of connections and the student level of competency. Male students consulted a lot of resources compared to female students. Male students may be qualified as "curious students" because they have consulted more resources compared to female students while they have all spent almost the same time on the LMS.

The login frequency to Moodle is higher on the assessment periods for most students with poor level of competency. According to a study [20], poor student levels of competency were associated with negative attitudes and perceptions about Moodle, while excellent level of competency were associated with increased use of LMS. Other factors come into play and influence student level of competency such as student motivation and engagement [17]. This raises questions about the extent to which data collected on an LMS is sufficient to understand student behavior.

Overall, if an analysis shows that students who accessed to the LMS only in the days preceding the assessment had unsatisfactory level of competency, it is necessary to create resources more adapted to their profiles to encourage them to access to the LMS on a regular basis.

6. CONCLUSION

The current paper presents a new way to study students' competencies mechanisms through the resolution of Learning and Evaluation Situations (LES). Student's level assessment is based on student's success in concrete and complex situations, and not on about learned techniques in classical courses. Conclusions generated through this study could help teachers to develop a variety of teaching strategies.

Presented findings give the possibility to profile students less engaged in online learning, teachers are able to conduct detailed observation during classroom sessions and identify the source of understanding problems and develop thereafter the appropriate teaching strategy to each situation and each student. If the resources provided on the LMS are not adequate for the student's profile, the teacher updates the LMS content. If problems are related to LES, teachers choose a less complex and adapted LES to student's profile. This process can be repeated as many times as required until the student completes required competency acquisition.

Offline behaviors account for a large proportion of the learning process, except that these are not explained by online student activity, making it difficult to predict a model. This result suggests that designing a complete dashboard helping teachers to adjust their teaching strategy, requires future studies making better use of blended learning mode by collecting both online student behavior and face-to-face learning data. In addition, to investigate the generalizability of the proposed approach, data analysis techniques should be applied in different disciplinal area over a long duration.

REFERENCES

1. S. Preidys and L. Sakalauskas, **Analysis of students' study activities in virtual learning environments using data mining methods,** *Technological and Economic Development of Economy*, vol. 16, no. 1, pp. 94–108, 2010.
https://doi.org/10.3846/tede.2010.06
2. R. S. J. D. Baker and K. Yacef, **The State of Educational Data Mining in 2009: A Review and**

Future Visions, *Journal of Educational Data Mining*, vol. 1, no. 1, pp. 3–16, 2009. https://doi.org/10.1016/j.compedu.2013.06.009

3. C. Romero, M. I. López, J. M. Luna, and S. Ventura, **Predicting students' final performance from participation in on-line discussion forums**, *Computers and Education*, vol. 68, pp. 458–472, 2013.
4. P. Long and G. Siemens, **Penetrating the fog: analytics in learning and education**, *Educause Review Online*, Vol. 46, No. 5, pp.31–40, 2011.
5. R. Ferguson, **Learning analytics: drivers, developments and challenges**, *International Journal of Technology Enhanced Learning*, Vol. 4, Nos. 5/6, pp.304–317, 2012. https://doi.org/10.1504/IJTEL.2012.051816
6. G. Siemens and R.S.D. Baker, **Learning analytics and educational data mining: Towards communication and collaboration**, *2nd International Conference on Learning Analytics and Knowledge, Vancouver, British Columbia, Canada*, pp.252–254, *29 April–2 May* 2012. https://doi.org/10.1145/2330601.2330661
7. F. Castro, A. Vellido, À. Nebot, F. Mugica, **Applying Data Mining Techniques to e-Learning Problems**. In: Jain L.C., Tedman R.A., Tedman D.K. (eds) *Evolution of Teaching and Learning Paradigms in Intelligent Environment. Studies in Computational Intelligence,* vol 62. Springer, Berlin, Heidelberg, 2007. https://doi.org/10.1007/978-3-540-71974-8_8
8. L. Rokach and O. Maimon, **The Data Mining and Knowledge Discovery Handbook: A Complete Guide for Researchers and Practitioners**, *New York: Springer*, 2005.
9. C. Romero, S. Ventura, and E. Garcia, **Data mining in course management systems: Moodle case study and tutorial**', *Computers & Education*, Vol. 51, No. 1, pp.368–384, 2008. https://doi.org/10.1016/j.compedu.2007.05.016
10. I. Kazanidis, S. Valsamidis, T. Theodosiou, and S. Kontogiannis, "**Proposed framework for data mining in elearning: the case of Open e-class**," *Proc IADIS Applied*, pp. 254–258, 2009.
11. P. Luik and J. Mikk, **What is important in electronic textbooks for students of different achievement levels?** , *Computers & Education*, Vol. 50 No. 4, pp. 1483-1494, 2008. https://doi.org/10.1016/j.compedu.2007.02.001
12. A. M. Mogus, I. Djurdjevic, and N. Suvak, **The impact of student activity in a virtual learning environment on their final mark**, *Active Learning in Higher Education*, vol. 13, no. 3, pp. 177–189, 2012. https://doi.org/10.1177/1469787412452985
13. C. Pislaru and R. Mishra, **Using VLEs to support student centred learning in Control Engineering Education**, no. January, pp. 457–461, 2014.
14. J. Champaign, K.F. Colvin, A. Liu, C. Fredericks, D. Seaton and D.E. Pritchard, "**Correlating skill and improvement in 2 MOOCs with a student's time on tasks**", *Proceedings of the First ACM Conference on Learning@ Scale Conference*, ACM, Georgia, pp. 11-20, 2014. https://doi.org/10.1145/2556325.2566250
15. M. Wen and C.P. Rosé, **Identifying latent study habits by mining learner behavior patterns in massive open online courses**, *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management, ACM*, pp. 1983-1986, 2014. https://doi.org/10.1145/2661829.2662033
16. D. Gašević, S. Dawson, T. Rogers, and D. Gasevic, "**Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success**," *Internet and Higher Education*, vol. 28, pp. 68–84, 2016. https://doi.org/10.1016/j.iheduc.2015.10.002
17. M. Cocea and S. Weibelzahl, **Log file analysis for disengagement detection in e-Learning environments**, *User Modeling and User-Adapted Interaction*, vol. 19, no.4, pp. 341–385, 2009. https://doi.org/10.1007/s11257-009-9065-5
18. M. Jovanovica, M. Vukicevica, M. Milovanovica and M. Minovica, **Using data mining on student behavior and cognitive style data for improving e-learning systems: a case study**, *International Journal of Computational Intelligence Systems*, Vol. 5, No. 3, pp.597–610, 2012. https://doi.org/10.1080/18756891.2012.696923
19. S. B. Kotsiantis, **Use of machine learning techniques for educational proposes: A decision support system for forecasting students' grades**, *Artificial Intelligence Review*, vol. 37, no. 4, pp. 331–344, 2012.
20. S. Kotsiantis, N. Tselios, A. Filippidi, and V. Komis, **Using learning analytics to identify successful learners in a blended learning course**, *International Journal of Technology Enhanced Learning*, vol. 5, no. 2, p. 133, 2013. https://doi.org/10.1504/IJTEL.2013.059088
21. L. Agnihotri, A. Aghababyan, S. Mojarad, M. Riedesel and A. Essa, **Mining login data for actionable student insight**, *International Educational Data Mining Society*, pp. 472-474, 2015.
22. A. Bovo, S. Sanchez, O. Heguy, and Y. Duthen, **Clustering moodle data as a tool for profiling students**, *2nd International Conference on E-Learning and Etechnologies in Education,* vol. 2013, no. September, pp. 121–126, 2013. https://doi.org/10.1109/ICeLeTE.2013.6644359
23. M. Mulder, **Conceptions of professional competence.** *International handbook of research in professional and practice-based learning*. Springer, pp. 107–137, 2014. https://doi.org/10.1007/978-94-017-8902-8_5
24. D. J. Camacho and J.M. Legare, **Shifting gears in the class-room—movement toward personalized learning and competency-based education**. *The Journal of Competency-Based Education,* vol. 1, no. 4, pp. 151–156, 2016. https://doi.org/10.1002/cbe2.1032
25. X. Roegiers, **Des situations pour intégrer les acquis scolaires.** Pédagogie en développement**,** 3ème édition Avril 2011.
26. A. Hachmoud, A. Khartoch, L. Oughdir and S. Kammouri Alami, **The Ontology of the**

Competency-Based Approach and the Perspectives of Implementation, *International Journal of Applied Engineering Research ISSN 0973-4562*, Vol 12, No 19 pp. 9099-9111, 2017.

27. M. TMIMI, M. Benslimane, A. Ibriz and K. Ouazzani. **Proposal of a complete model and architecture of an intelligent adaptive hypermedia**, *International Journal of Advanced Trends in Computer Science and Engineering*, Vol. 8, No.4, July –August 2019. https://doi.org/10.30534/ijatcse/2019/70842019
28. C. Romero, J. R. Romero, S. Ventura, and Á. D. Á. **Data, Educational Data Mining**, vol. 524. 2014.