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Classification of Students' Performance in a Learning Management System Using their eLearning Readiness Attributes

Ellenita R. Red[a*], Hanna Grace S. Borlongan[b], Tesalonica T. Briagas[c]
and Ma. Jonessa M. Mendoza[d]
College of Computer and Information Science, Malayan Colleges Laguna
PuloDiezmo Road, Cabuyao, Laguna 4025, Philippines
*Corresponding Author: **erred@mcl.edu.ph**

ABSTRACT

Technologies provide opportunities for higher education institution to enhance the learning environment of the students as well as the management and administration of program, module delivery and support. One of the enhancements of the learning environment is the introduction of eLearning through the use of a Learning Management System (LMS) such as MOODLE or Edmodo. Malayan Colleges Laguna (MCL) aims to be at par with the global trend in the society when it comes to higher education and has already implemented blended learning approach at the second year of its operation in 2008. In its quest for quality and excellence through the utilization of technology, a concern on the usefulness and relevance of the technology being used needs to be assessed to better fit it to the learning culture of the students and faculty members. The main objective of this study is to classify the performance of students in a learning management system using their eLearning readiness attributes. The readiness attributes consists of technical skills, technical access, and attitudes of the students towards eLearning and the learning styles of the students. Data mining techniques has been implemented to describe and classify the performance of studentsusing their eLearning readiness attributes, specifically clustering and classification techniques are used. A total of four-hundred fifty-two studentsare selected to participate in the study and these students used either MOODLE or Edmodo as an LMS.The final grades of the students are asked from their respective instructors and areused as classifier.The datasetare pre-processed and analyzed usingan open source machine learning softwarecalled Waikato Environment for Knowledge Analysis(WEKA). The results show that the following attributes are significant in order for students to thrive in a blended learning approach: age, computer access, access on tools, computer skills, abilities, motivation, and time management.

Keyword: eLearning, Blended Learning, Learning Management System, MOODLE, Edmodo,Educational Data Mining

1. Introduction

The advancement and availability of technologies are something that should be explored by academic institutions in order to enhance the learning environment of the students. One of the enhancements of the learning environment is the introduction of eLearning. There are many definitions of eLearning, Wentling et.Al. (2008) defines eLearning as “the acquisition and use of knowledge distributed and facilitated primarily by electronic means. The Commission on Technology and Adult Learning (2001), describes it is an instructional content or learning experiences delivered or enabled by electronic technology. In practice, it incorporates a wide variety of learning strategies and technologies. Another Author, Marc Rosenberg (2001) confines eLearning to the internet as “the use of internet technologies to deliver a broad array of solutions that enhance knowledge ad performance.”According to Mercado (2008), the need to acquire and to provide students knowledge and skills beyond geographic borders drives higher education institutions to an astute state of cogitation and an eLearning environment is composed of stakeholders, including the teachers, students, and administration. Similarly, according to Red, Borlongan, Briagas, and Mendoza (2013), the inclusion of the preferred learning styles of students is necessary for the successful implementation of eLearning.

Universities use different Learning Management Systems (LMSs) to make this eLearning to happen. These LMSs offer a lot of methods for the distribution of information and communication between the participants on a course. They allow instructors to deliver assignments to the students, produce and publish educational material, prepare assessments and tests, tutor distant classes and activate archive storage, news feeds and students’ interaction with multimedia. They also enhance collaborative learning with discussion forums, chats and wikis (Romero, 2010). Some of the most popular open source Learning Management Systems includes Edmodo and MOODLE which provide online activities for students with MOODLE having an advantage since the administration and controlcan be handled by the institution to do further analytics such as tracking web logs of students for further monitoring of their progress and other activities (Red, Cancino, Hanrath, and Ricardo, 2014).However, having the right technology is not enough for an eLearning environment to become successful. Universities must consider a number of important issues when considering the implementation of eLearning regardless of the LMS used. The literature suggested that it is necessary to do a readiness assessment of the different stakeholders who are involved in this eLearning activity which include: students, faculty members, school administrators and facilities (Mercado, 2008); technology access (Fathaigh, 2002), technology skills and attitude (Oliver, 2001) and learning style (Esichaikul and Bechter, 2010). The eLearning readiness criteria provides a goal for the institution as it develops its capability to implement an online learning environment. Being able to assess the status as to where the institution is currently positioned in relation to where it envisions itself to be already sets a milestone. Having this vital information already sets the institution to develop strategies as well as timetable for achieving readiness in all the categories identified.

Assessment of the different stakeholders is not an easy task for anyinstitution since major activities are focused mostly in academics. Lack of personnel and tools are just some of the issues that are usually encountered in the implementation of this task. Nevertheless, technology found its way in solving these problems in terms of collection and analysis of the data that will be generated in assessing the readiness of the these stakeholders. A technique being adopted by the educational system from the world of business to solve these concerns is Data Mining. Data mining, also called Knowledge Discovery in Databases (KDD), is the field of discovering novel and potentially useful information from large volume of data (Fayyad, et al, 1997). Clustering is a data mining technique with the goal of finding data points that naturally group together, splitting the full data set into a set of groups, called clusters. This method was based on distance concepts among individual participants and was intended to gather individuals who were close into the same group (Roiger & Geatz, 2003). Another data mining strategy is data classification. The aim of classification is to separate different data into different pre-defined classes. Classification is based on available features that leads to new data description and causes a better understanding of each class in a database or in a data warehouse, so classification can prepare a model to describe the proper class for any given data. Different statistical techniques are used for classification functions like Bayesian, Neural Network, Decision Tree and Support Vector Machine. Prediction methodology using Decision Tree was used, it works as a classifier to classify instances by sorting them down the tree from the root to leaf nodes (Quinlan, 1986).The Decision Tree technique was used to build a predictive model for online learning performance (Hung & Ke, 2008) and its purpose is to classify the data into distinct groups or branches that generate the strongest separation in the values of the dependent variable (Kularbphettong & Tongsiri, 2012).In addition, the Naïve Bayesian classifier was used since it provides a simple and effective approach to classifier learning. It assumes that all class-conditional probability densities are completely specified (Jain et al. 2001). To further improve the accuracy of the models, feature selection was implemented. Feature selection in supervised learning has a main goal of finding a feature subset that produces higher classification accuracy (Ramaswami & Bhaskaran, 2009). In the summary of stratified cross validation, this part of the output gives the estimates of the tree's predictive performance, generated by WEKA's evaluation module. This part, outputs the list of statistics summarizing how accurately the classifier was able to predict the true class of the instances under the chosen test module.Effectiveness of the algorithms is presented in terms of different measures like ROC Values and F1-Measure values(Ramaswami & Bhaskaran, 2009).

Furthermore, the availability of the internet provides a venue that can be accessed by these stakeholders anytime and anywhere thus a website was built to gather data of these stakeholders. The data gathered can be classified in meaningful and useful classes. Also, the prediction of the learner's studying result based on the current model may help the faculty member prepare a suitable learning plan for the learners and be able to monitor the learners studying progress.The following eLearning readiness attributes was used in the study: technological access, technological skills, attitude, and the addition of learning styles. Learning styles was included since the eLearning platform should give personalization for the learner; one way is to offer the specific learning material to the learner based on the learner's learning styles (Peter, et al.

2010).Also, the final grade of the students was used as classifier for the predictive model of the eLearning performance of the students. A machine learning tool used wasWaikato Environment for Knowledge Analysis (WEKA), WEKA is a collection of machine learning algorithms for data mining tasks.

Malayan Colleges Laguna (MCL) aims to be at par with the global trend in the society when it comes to higher education. Thus, there is a unit assigned to handle the academic support dedicated to the advancement and enhancement of the teaching – learning atmosphere in MCL. Malayan Colleges Laguna – Learning Environments and Innovations (MCL-LEI) helps to provide context to the design and development of educational and training materials and/or program based on the set initiatives of MCL. Although the office has just been established in school year 2013, MCL has been implementing blended learning, a face-to-face classroom interaction with an eLearning approach since 2008. However, based on the data provided by MCL-LEI, the online courses showed minimal access and usage. Out of the 672 sections per course offered in MCL only 196 or 20.83% of the sections are being utilized in MOODLE for the SY 2012-2013. Now, MCL-LEI is looking into these critical success factors that would help the students to thrive successfully in an eLearning environment regardless of the LMS used. Thus, this study gave answer to the question “What are the eLearning readiness attributes that can improve the eLearning Performance of Students?” The main objective of this study was to explore the eLearning readiness attributes that may impact the study outcome in an eLearning environment to improve the current blended learning implementation setup by MCL. This issue has yet to be examined so far for MCL and this paper attempted to fill in this gap. The objectives of the study were: (1) develop a website for the collection of eLearning readiness attributes data; (2)cluster the eLearning readiness attributes of students according to their performance; and, (3) build prediction model of study outcome using the eLearning readiness attributes regardless of LMS used.The application of data mining and machine learning tools enabled the institution to analyze the eLearning readiness attributes of the students that can be disseminated to faculty members so that they would be able to adjust the activities and resources that they will put into their online courses. Also, through the information provided, the online course can now be made to best fit the students’ behavior (Esichaikul and Bechter, 2010).

2. Methodology

Malayan Colleges Laguna is currently using blended learning which is face-to-face classroom interaction with an eLearning approach. The office that handles the academic support dedicated to the advancement and enhancement of the teaching-learning atmosphere is MCL-LEI and they handle the administration of MOODLE, the main Learning Management System of the institution. However, there are other LMSs used by the professors such as Edmodo. Edmodo is a social learning community where teachers, students, and parents can connect safely and securely with the goal of helping connect all learners with the people and resources they need to reach their full potential. In this study, faculty members who used either MOODLE and Edmodo in their classes as a tool for blended learning were identified and selected to participate. Also, the extent of the use of the LMSs were considered and faculty members that were selected should at least were able to utilize forum, quiz, and assignment activities and uploaded materials or web links in their LMSs courses.

The study used a simple input-process-output framework as shown in figure 1, the input part consisted of assessment tools in a form of a quantitative design and was conducted as a descriptive survey. These tools covered the entire criteria needed to evaluate the students in using the Learning Management Systems (LMS).The survey was conducted using online and offline survey.

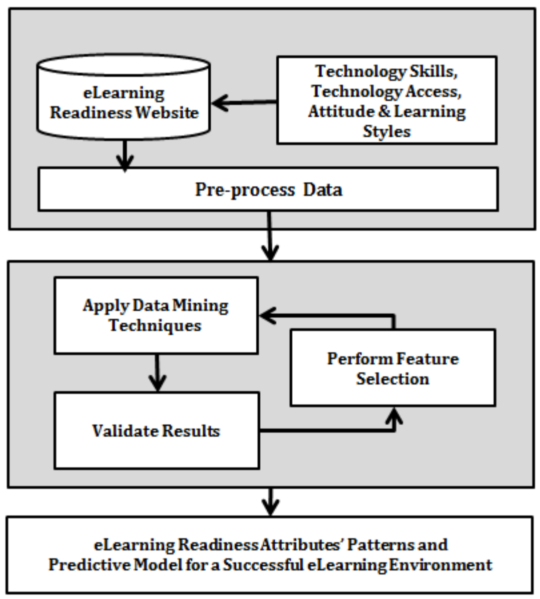

Figure 1. Conceptual Framework

To contain the online survey for the students, a website was prepared and created using PHP as the programming language and MySQL as the database. This survey was delivered online for faster extraction of data needed for pre-processing. For students who used MOODLE as their LMS, with the help of faculty members they posted the link in their MOODLE course.The advantage of having it online was that the data was extracted easily and the computation of mean and assessment of the student's learning style was embedded in the system. Figure 2 and 3 shows the interface of the developedwebsite. On the other hand, the students who used Edmodo took the offline or pen-and-paper survey.

Figure 2.Web site interface showing the technology access questions

Figure 3.Web site interface showing the learning style questions

Surveys were performed to acquire insights and feedback of the students prior to using the Learning Management Systems. For this study, a total of 452 students answered the survey and these were the students who were using the blended learning approach. There are 337 students who used MOODLE and 115 students used Edmodo. The instrument used consists of: demographic profile of students, eLearning readiness assessment which includes technical skills, access, and attitudes of students and leaning styles. The attitude of the students includes study habits, motivation, and time management. For study habits, motivation and time management, these attributes were converted from numerical to nominal data using a scale. The survey assessed technology access and skills of the students if they have the ability to participate in an eLearning environment as well as reflect on their learning styles and their attitude towards eLearning. The strength of this tool was already based on different related literature regarding the online behavior and characteristics of students. However, the learning styles of students was added to the study. To assesss the learning styles of students, the study made use of Kolb's Learning Styles. Kolb has described four basic learning styles: accommodative, assimilative, divergent, and convergent. Incorporated within each learning style is a combination of two of the four learning modes: Concrete experiences, reflective observation, abstract conceptualization, and active experimentation(Kolb, 1984).The final grades of the students were also gathered at the end of the term and were used in the prediction of the performance of the students towards eLearning environment. An interview with MOODLE's Administrator was also conducted to validate some questions regarding the functions and goals of MCL-LEI and provided the statistics generated from MOODLE or the LMS used by the institution.

Pre-processing happened after accomplishing the target number of surveys. In pre-processing, the online survey were saved to the database in a form of a data set and this data set were combine to the data set of the offline pen-and-paper survey to form the final data set for analysis.Two data mining techniques were used in the processing phase which are clustering and classification. Clustering methodology was used to categorize students into homogeneous groups and K-means algorithm was applied to group students based on their shared characteristics: technology skills, technology access, attitudes and learning styles and for prediction methodology a Decision Tree and Naïve Bayesian classifiertechniques were used.For validation, a 10-fold cross-validation was used, the data was divided into 10 blocks containing roughly equal numbers of cases and class-value distributions. The average performance on the tests was then used to predict the true accuracy of the model from all the data. In order to determine the significance or importance of an attribute in terms of interrelation among other attributes,Feature selection techiniquewas used. Feature selection has proven in both theory and practice to be effective in enhancing learning efficiency, increasing predictive accuracy and reducing complexity of learned results. The output of the study is expected to provide the patterns or behaviour of students that may help them succeed in the blended learning approach being provided by the institution.

3. Results and Analysis

In determining the performance of the students, the study was able to identify the different attributes that affects students' learning. Table 1 presents the list of attributes that were gathered from the students through the help of the faculty members. It includes the demographic profile of the students and their individual assessment in terms of technology access, technology skills, attitudes and learning styles and the final grades of the students from their respective professors.

Table 1
Final Summarization Table Attributes

	Attribute	Description
1	LMS	LMS used in a course (MOODLE or Edmodo)
2	Age	The age of the student
3	Gender	The gender of the student (male or female)
4	Computer Access	The student’s access on computers at home and in school
5	Internet Access	The student’s internet access at home or in school
6	Access on Tools	The student’s access on needed hardware (i.e. printer)
7	Computer Skills	Skill of student in basic computer use
8	Internet Skills	Skill of student in the use of internet
9	Software Skills	Skill of student in the use of common software applications
10	Study Habits	The study habits of student
11	Abilities	The capability of the student to perform assigned tasks
12	Motivation	The students’ willingness to study
13	Time Management	Assessment on how the student manages time in studying lessons
14	Learning Style	Assessment of the learning style of the student (convergent, divergent, assimilative, accommodative)
15	Final Grade	Student's final grade in numerical form which was used as classifier
16	Remarks	Student’s final grade remarks either passed or failed

3.1 Demographic Profile of Respondents

The data for the final summarization table was gathered through the use of a website and through the means of pen-and-paper. The final respondents are 452 records after removing incomplete or duplicate data. The LMS used in specific course is either MOODLE or Edmodo where 337 of the respondents are using MOODLE and the other 115 are using Edmodo. Fifty percent of the respondents are males while the other fifty are females. Most of the respondents are from the age group of 16 to 17 year olds. A total of 347 students or around 76.77% of the students passed their respective course leaving 105 students or about 23.23% who failed their respective course.

3.2 Analysis Using Initial Attributes

Using the initial data set, table 2 presents three clusters:cluster 0, the high performing cluster, cluster 1, the average performing cluster while cluster 2 was the low performing cluster. In describing the Full Data, the LMS commonly used was MOODLE. The average age of this cluster is 18, also majority of students in this cluster are male students. In general, students who participated in the study have the technical skills and access but must work on their study habits, motivation, and time management. The learning style of the entire cluster is accommodative and an average of 65.49%.

Table 2
Clustering Results Using Initial Attribute

Attribute	Full Data	Cluster 0(35%)	Cluster 1(37%)	Cluster 2(28%)
LMS	MOODLE	MOODLE	MOODLE	MOODLE
Age	18	18	20	17
Gender	M	F	M	M
Computer Access	Always	Always	Always	Usually
Internet Access	Usually	Always	Usually	Usually
Access on Tools	Always	Always	Always	Always
Computer Skill	Always	Always	Always	Always
Internet Skill	Always	Always	Always	Always
Software Skill	Usually	Usually	Always	Usually
Study Habits	Usually	Always	Usually	Usually
Abilities	Always	Always	Always	Always
Motivation	Usually	Usually	Usually	Usually
Time Management	Usually	Usually	Usually	Usually
Learning Style	Accommodative	Accommodative	Convergent	Divergent
Final Grade	65.49	67.49	66.14	60.29
Remarks	PASSED	PASSED	PASSED	PASSED

The biggest cluster or the average performing group is cluster 1 with 37%, following closely is cluster 0 or the high performing group with 35% and the low performing group which consisted of 28% of the participants. In terms of age, cluster 1 exhibited the more mature age while cluster 2 consisted mostly of students aged 17. Majority of the gender for the average performing and low performing clusters are male while the high performing cluster are female students.As for the technology access and skills, the low performing group do not have access to computer and internet as compared to the other two clusters. The attitude of the high performing cluster clearly showed that they have good attitude towards eLearning as compared to the average and low performing clusters. Lastly, the three clusters have distinct learning styles, the high performing cluster is accomodative, the average performing cluster is convergent, and the low performing cluster is divergent.

3.3 Classification Analysis on Attributes after using Feature Selection

The main objective of feature selection is to choose a subset of input variables by eliminating features, which are irrelevant or of no predictive information. There are six feature selection techniques used: Correlation-Based Attribute Evaluation (CB), Chi-Squared Attribute Evaluation (CH), Gain-Ratio Attribute Evaluation (GR), Information-Gain Attribute Evaluation (IG), Relief-F Attribute Evaluation (RF) and Symmetrical Uncertainty Attribute Evaluation (SU). Different techniques provide different results for each set, meaning each of them accounts the relevance of the attributes in a different way. Table 3 presents the six techniques, the number of attributes for each technique, and the attributes that are relevant, also the results forJ48 algorithm and Table 4 shows the results for NB algorithm.

Table 3
Accuracy using different Feature Selection Techniques for J48

Feature Selection Technique	Number of Attributes	Attributes	J48		
			Accuracy	Kappa Statistic	ROC Area
CB	2	Age, Access on Tools	76.76%	0	0.485
CH	8	Age, Computer Access, Access on Tools, Computer Skills, Abilities, Motivation, Time Management, Remarks	75.66%	0.0537	0.55
GR	8	Age, Computer Access, Access on Tools, Computer Skills, Abilities, Motivation, Time Management, Remarks	75.66%	0.0537	0.55
IG	6	Age, Computer Access, Access on Tools, Computer Skills, Abilities, Motivation, Remarks	75.22%	-0.0004	0.51
RF	5	Age, Gender, Computer Access, Internet Access, Remarks	75.22%	0.0149	0.55
SU	6	Age, Computer Access, Access on Tools, Computer Skills, Motivation, Remarks	76.76%	0	0.45

In comparing the data, J48 algorithm has the accuracy of 75.66%, kappa statistic is 0.0537 and ROC area is 0.55 and for NB algorithm the accuracy is 75.88%, kappa statistic is 0.3125 and ROC area is 0.69and the feature selection that stood out are Chi-Squared Attribute Evaluation (CH) and Gain-Ratio Attribute Evaluation (GR). The final attributes that was used for classification of students' performance in an eLearning environment are:age, computer access, access on tools, computer skills, abilities, motivation, time management, and remarks. However, in the final selection of algorithm, NB was selected since it performed better in terms of kappa statistic as compared with J48 algorithm and itshowed stronger relation between the class values and the CH or GR selected attributes.

Table 4
Accuracy using different Feature Selection Techniques for Naïve Bayes

Feature Selection Technique	**Number of Attributes**	**Attributes**	**NB**		
			Accuracy	**Kappa Statistic**	**ROC Area**
CB	2	Age, Access on Tools	74.77%	0.2426	0.678
CH	8	Age, Computer Access, Access on Tools, Computer Skills, Abilities, Motivation, Time Management, Remarks	75.88%	0.3125	0.69
GR	8	Age, Computer Access, Access on Tools, Computer Skills, Abilities, Motivation, Time Management, Remarks	75.88 %	0.3125	0.69
IG	6	Age, Computer Access, Access on Tools, Computer Skills, Abilities, Motivation, Remarks	74.55%	0.3289	0.688
RF	5	Age, Gender, Computer Access, Internet Access, Remarks	74.33%	0.2899	0.675
SU	6	Age, Computer Access, Access on Tools, Computer Skills, Motivation, Remarks	74.55%	0.2937	0.685

The confusion matrix shown in table 5 which was generated by Naïve Bayes algorithmshows the distribution of the instance classifications. Out of the 105 students who failed, 57 instances have been misclassified as ‘Passed’ and from the 347 students 52 of them were misclassified as ‘Failed’.

Table 5
Confusion Matrix of NB

Naive Bayes		
a	b	<--classified as
48	57	a=FAILED
52	295	b=PASSED

4. Conclusions and Recommendations

In this study, data mining algorithms were applied to determine the eLearning readiness attributes of the students to be able to improve the eLearning environment of the institutions. To be able to address the problem, objectives of the study were established. The main objective of the study aimed to explore the eLearning readiness attributes that may impact the study outcome in an eLearning environment at Malayan Colleges Laguna. Also, three specific objectives have been decomposed in order to perform the general objective: (1) a website was created using PHP as the programming language and MySQL as the database; this website contains the survey for students. The final summarization table contains the online and offline survey that was analyzed using a machine learning tool WEKA; (2) the performance of the students was clustered using the initial datasetand the results have shown that thereare three clusters: the high performing students, the average performing students and the low performing students. In terms of technology access, the low performing cluster answered they do not have the access to computer and the internet which are important aspect of eLearning otherwise students will not be able to perform the activities assigned by the faculty members. Age seemed to be significant with the eLearning attributes since most the low performing cluster is the youngest among the group. The gender of the students is also noteworthy since the high performing cluster consists mainly of female students and this cluster also exhibited the right combination of attitude to thrive in an eLearning environment.Lastly, faculty members must be able to address the different learning styles of students, giving particular attention to students with divergent as learning style since this is the low performing cluster; (3) to enhance the predictive model feature selectionwas performed on the initial data set.It was used to find the best attributes that will produce higher classification accuracy for J48 and Naïve Bayes algorithms and the algorithm that was best suited for the data set is Naïve Bayes. Finally, to answer the main problem,"What are the eLearning readiness attributes that can improve the eLearning Performance of Students?" feature selection was performed on the initial data setresulting to seven eLearning attributes:age, computer access, access on tools, computer skills, abilities, motivation, and time management.

The study can be repeatedevery term and the data set produced here can be used as training set to better improve the predictive model of the students' performance in the LMS. Different algorithms may also be utilized in performing classification. Clusters may also be described using visualization tools for easy understanding and clearer presentation of the data set. Involve more faculty members in the study so that more data can be generated and analyzed and train faculty members on how to perform the assessment on their own so that they have a firsthand knowledge of their students' eLearning readiness state. Also, educational data mining can be performed in other data produced by the students for the improvement of students' services such as the data produced in students' admission, guidance, and other online services of Malayan Colleges Laguna.

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