A GENERALIZED E-LEARNING USAGE BEHAVIOUR MODEL BY DATA MINING TECHNIQUE

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ABSTRACT

Current study on e-Learning user's behaviour model obtained the specific models. In many cases, the e-Learning user's behaviour model for open source e-Learning system such as Moodle, which can predict learning outcome or learning performance is still deficient and cannot generally apply in many institutions due to the fact that the majority of prediction models were developed particularly for certain institutions. This study proposes to produce a general model that can make a prediction of learning outcome inspired by Skinner's theory, which explains the relationship between learner, achievement, and learner reinforcement. This study proposes similar patterns in e-Learning user's behaviour models of different institutions by the data-mining technique based on the learning environment theory. Therefore, this research is conducted in three main phases; include data preparation from weblog of different institutions with the same e-Learning system, data extraction by the accurate classifier model finding process and model verification for generating a verification pattern. The research outcome will be a similar pattern that could be used as a direction for creating a more appropriate e-Learning users' behaviour model and could be used broadly in other higher institutions.

Keywords: e-Learning, user behaviour, data mining.

INTRODUCTION

In many academic institutions as well as commercial organizations, the system that can support and improve learning within an organization and institution nowadays is continuously developing, particularly, the Learning Management

System (LMS) nowadays plays more crucial roles in distance learning because of its manageability. This system is notably able to manage the registered users, manage course catalogues, record data from learners and is equipped with reports for the system management. For distance-learning education, the LMS software is very economical and practicable. Besides that, this software can be used in many different phases that can support users in terms of performing content preparation by keeping the users' records. An advantage of the LMS open source software is its simple database structure adapting especially a usage history structure so-called web- log. The web log is a hidden useful part, which is a helpful factor for developing a stable and appropriate e-Learning users' behaviour model by using the data-mining technique. To strengthen the e-learning system, Moodle (2011) continuously tries to improve the implementation problem while adding more new diverse functions to fulfill the users' needs. There are several works that attempt to improve and develop the novelty in various features for its new version which can be catagorized into two aspects as e-Learning tools and e-Learning users' behaviour models (Figure 1).

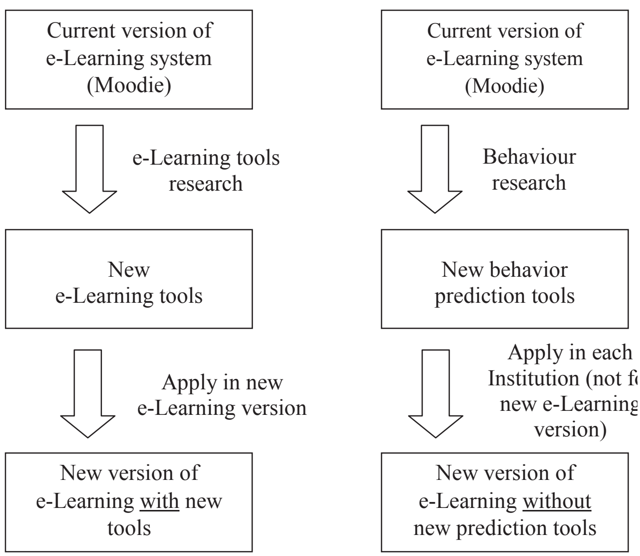

Figure 1. Gap of e-Learning users' behaviour model development (a) the Current Model and (b) the New Model.

As depicted in Figure 1, e-Learning tools are the functions for enhancing on-line learning effectiveness which is synthesized and developed by interested users. After that, it will be set up for wide usage, in which it can be downloaded by general users as shown in Figure 1(a). However, those models could not be applied in other higher institutions that have limitations to develop their own suitable models for enhancing learners' performances broadly. Furthermore, the developed e-Learning users' behaviour models could not be applied to the newer version for the open source e-Learning system tools that are shown in Figure 1(b).

Accordingly, some researchers in the higher institutions (Lingyan, Jian, Lulu, & Pengkun, 2010; Ribeiro & Cardoso, 2008) used their web-logs for developing appropriate and efficient models only for particular uses. Meanwhile, the study of the e-Learning users' behaviour evaluation enables the new model related to learning behaviour and effect, to be used to evaluate students in their e-Learning system (Lingyan, Jian, Lulu, & Pengkun 2010). Accordingly, the researchers on e-Learning users' behaviour models, mentioned that, e-Learning models are very helpful for either the teachers or the learners to realize the learning status and learning outcomes for learners' higher achievement (Chien Ming, Chao Yi, Te Yi, Bin Shyan, & Tsong Wuu, 2007; Chun Xia, Hui Bao, Chang Yi, & Yue Xing, 2010; Ribeiro & Cardoso, 2008). Nevertheless, the studies of the similarities of the e-Learning users' behaviour models from different higher institutions are deficient. Therefore, understanding the relationship between two different models could be studies based to on their similar patterns that would be useful for gaining the knowledge to develop an appropriate universal model.

E-LEARNING THEORY

There are a few theories related to learning behaviour such as the classic Skinner learning theory (O' Donohue & Ferguson, 2001), which describe the development of an effective technology of teaching as his most important practical effort. In the technology of teaching, Skinner saw teaching not as an art but as an applied science that could benefit from his operant research. Skinner thought that traditional teaching methods violated the laws of learning. Skinner argued that learning should be evaluated and shaped towards the pedagogical objectives. According to Skinner, in traditional teaching methods, rewards (e.g., grades) are typically too remote in time to serve as effective reinforces for newly- acquired behaviour. Skinner thought that reinforcement was too scarce in traditional schools, and he thought that schools relied on aversive control, which taught students to dislike and avoid learning, at least in unsuccessful subjects. The goal of education is to build behavioural repertoire, not to suppress behaviour, and thus reinforcement should be stressed. According to Skinner's theory, the learning environment is important to change a learner's behaviour as the e-Learning environment is important to change a e-Learning user's behaviour. This study proposes a behaviour model that can predict learner achievement on the e-Learning system.

e-Learning is comprised of a wide range of disciplines such as education, management, psychology, sociology, communications, library science, information science, social studies of science, social studies of technology and computer science. Therefore, the study of e-Learning should assemble these related supporting theories. In this new era of learning, a new learning theory is required as mentioned in Haythornthwaite & Andrews (2011) at least because of three reasons. Firstly, if we accept the premise that learning is socially situated, and that e-communities are different from conventional learning communities in classrooms in schools and universities, then it follows that e-Learning is different from conventional learning. Secondly, the nature of knowledge itself is affected by digital technology, particularly in the leveling out of the relationship between existing knowledge, the teacher, and the student. Rather than a hierarchical conception of knowledge, e-Learning and its technologies promote a flatter, more democratic, more potentially dialogical relationship between the learner and knowledge. Thirdly, transduction is easier with a multimodal computer interface than without it. Transduction is an aspect of transformation, which in itself is a major aspect of a learning theory. However, there is still no new e-Learning theory. At the same time, researchers are working to enlarge knowledge based on the e-Learning theory. For this reason, e-Learning study is still based on the learning theory. Particularly, the behaviour theory of Skinner is the basis for the e-Learning user's behaviour study because this theory can explain most of the learner's behaviour that affects the learner's outcome in terms of reinforcement for learning achievement.

The aim of the study is also to demonstrate the relationship between the e-Learning user's behaviour model from different institutions in order to develop a more suitable and predictable e-Learning user's behaviour model. At the same time, the latest output model of this study should be the general model that can apply for other higher institutions. For the general model, it could be demonstrated by the motivation factor inside the e-Learning system that it is the high student's motivation in e-Learning technology compared with traditional learning (Rashty, 1999). Hence, the e-Learning functions as the positive reinforcement to create higher motivation in the learner as mentioned by Cotton (1995) that reinforcement is the cause of motivation as shown in Figure 2.

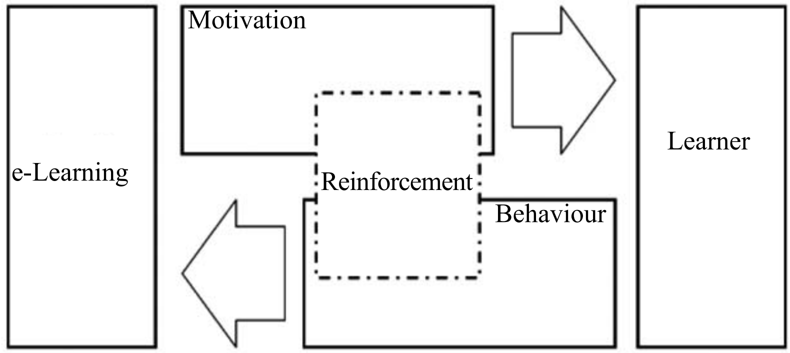

Figure 2. e-Learning and learner relationship based on Skinner Theory.

Figure 2 shows that reinforcement is the cause of learner motivation from e-Learning while it is the cause of learner behaviour. Based on the same e-Learning system, they are the same inside functions as reinforcement that could motivate the learner to achievement. Thereby, it should be the same trend of learning outcome from different higher institutions based on the same e-Learning system. The same trend of learning outcome is the most interesting for this study in terms of discovering a similar pattern from different e-Learning user's behaviour models. This similar pattern will be used in the further development of the general e-learning user's behaviour model.

E-LEARNING

e-Learning has become an important part of the learning system. Currently, there is an increasing interest in data-mining and educational systems, making educational data-mining a new growing research community. The popularity of e-Learning has grown rapidly over the last decade in higher education (Dai & Zhang, 2008). The e-Learning system allows students to learn the lecture materials, and experience the learning process through the network (Min, 2005). At the moment, e-Learning is remarkably developed in order to produce effective learning outcomes. This advanced system meets the learning activities in reality. Furthermore, it also creates virtual classroom management systems, for instance user authentication and classroom communication in order to foster an efficient virtual classroom.

The Learning Management System (LMS) is a system software for learning that enables the display of theoretical content in an organized and controlled way. It mainly consists of administration, content packing, synchronous and asynchronous communication tools, knowledge evaluation, and tracking users (Sancristobal et al., 2010). LMS provides a platform to allow interactions between students and tutors, as well as among the peers. Most of the conventional pedagogic activities can be performed in the e-learning environment (Hsien Tang, Chih Hua, Chia Feng, & Shyan Ming, 2009). At the same time, higher institutions look for the best LMS open source that best suits commerce. However, most LMS are being developed to meet the standard pattern that can be used with other systems such as Sharable Content Object Reference Model (SCORM) (scorm.com, 2012), that is a collection of standards and specifications for web-based e-Learning and it is the most famous standard pattern.

OPEN SOURCE E-LEARNING

Nowadays, the number of open source e-Learning systems is increasing including the Modular Object-Oriented Dynamic Learning Environment (Moodle) (Moodle.org, 2011), which is known as one of the best LMS because it has been designed based on social constructionist pedagogy. It has been widely adopted in 200 countries, has more than 40,000 registered sites, and the number of courses is in excess of 2,400,000 (Hsien Tang et al., 2009). Moodle is a free web-based application Course Management System (CMS) used by educators in creating effective online learning sites. These open source LMS contents are suitable for the standard Sharable Content Object Reference Model (SCORM) (scorm.com, 2012; Ruiz Reyes et al., 2009). Thereby, the study on open source e-Learning user’s behaviour could be broadly advantageous.

Table 1 presents the main activities that appear in most of today’s open source e-Learning systems that could be used for e-Learning users’ behaviour in web-log. The web-log in Moodle LMS is not only important as a navigational framework but it also provides relevant input for selective model construction which is crucial for tracking students’ behaviour. This represents its successful ability to predict students’ final outcomes while providing useful feedback during the course.

Learning Behaviour

Kebin, Feimin, Ming, Feng, and Xiaoshuang (2008) define e-Learning behaviour as the long-distance independent learning behaviour that takes place in the learning environment which is constructed by information technologies. The learning portfolio is the e-Learning user’s behaviour data that provide the students with a specific method to evaluate their own learning situations.

They include all records of the students' activities during the learning process, such as their interaction with others, assignments, test papers, personal work collections, their discussion content, and online learning records (Chien Ming et al., 2007). The structure of the database from the open source e-Learning system is illustrated in Table 2.

Table 1

Activities of Open Source e-Learning Group by Subcategories (Graf & List, 2005).

Subcategories	Activities
Communication tools	Forum, Chat, Mail/Messages, Announcement, Conferences, Collaboration, Synchronous & asynchronous tools
Learning objects	Tests, Learning material, Exercises, Other creatable LOs, Importable LOs
Management of user data	Tracking, Statistics, Identification of online users, Personal user profile
Usability	User-friendliness, Support, Documentation, Assistance
Adaptation	Adaptability, Personalization, Extensibility,
Technical aspects	Standards, System requirements, Security, Scalability
Administration	User management, Authorization management, Installation of the platform
Course management	Administration of courses, Assessment of tests, Organization of course objects

Note: Adapted from "An evaluation of open. Source e-learning platform stressing adophen issues", by Graf & List, 2005.

Table 2

Important Moodle Tables for Doing Data Mining (Romero, Ventura, & Garcia, 2008).

Name	Description
mdl_user	Information about all the users.
mdl_user_students	Information about all students.
mdl_log	Logs every user's action.
mdl_assignment	Information about each assignment.
mdl_assignment_submissions	Information about assignments submitted.
mdl_chat	Information about all chat rooms.
mdl_chat_users	Keeps track of which users are in which chat rooms.

(continued)

Name	Description
mdl_choice	Information about all the choices.
mdl_glossary	Information about all glossaries.
mdl_survey	Information about all surveys.
mdl_wiki	Information about all wikies.
mdl_forum	Information about all forums.
mdl_forum_posts	Stores all posts to the forums.
mdl_forum_discussions	Stores all forum discussions.
mdl_message	Stores all the current messages.
mdl_message_reads	Stores all the read messages.
mdl_quiz	Information about all quizzes.
mdl_quiz_attemps	Stores various attempts at a quiz.
mdl_quiz_grades	Stores the final quiz grade.

Note: Adopted from "Computer & Education", 51 (1), 368-384 by Remero, Return & Garcia, 2008.

In order to make an e-Learning user behaviour more explicit, the developed e-Learning users' behaviour model should be generic for generalization. Some researches design a kind of active e-Learning system that is based on students' requirements and propose the workflow of the system and design the function modules of the active e-Learning system. The designs focus on students activeness and include the most active learning functions or tools of e-Learning (Chun Xia, Hui Bao, Chang Yi, & Yue Xing, 2010). For this reason, it is crucial to discuss the actual e-Learning users' behaviours in order to generate the useful model that can be generalized in e-Learning development. There are many important data tables for e-Learning usage behaviour study such as learner information, learner's action log and learner studying activities as shown in Table 2 which contains the necessary data for the data-mining process. A collection of normal web-log could help to explain the phenomenon of the e-Learning users' behaviour comprehensively. In addition, it explains the e-Learning users' behaviour in different periods of time and different user groups that is suitable for many data-mining technique algorithms.

User Behaviour Model Development

The data derived for this study concerned the e-Learning users' behaviour that could affect model analyzing from the data mining technique to be more stable and more generalized. Therefore, the study of this information would be used to develop a more stable and more effective model of e-Learning users' behaviour. In order to construct a prediction model, these web logs are exploited for creating a useful model to determine e-Learning users' behaviour. Figure 3 shows that the process of the proposed approach consists of three steps:

1. Data preparation process where the data sources are derived from.
2. Data extraction process that uses data mining techniques to find out the best models.
3. Model verification process that verifies the output models from step two and the other model from another e-Learning system.

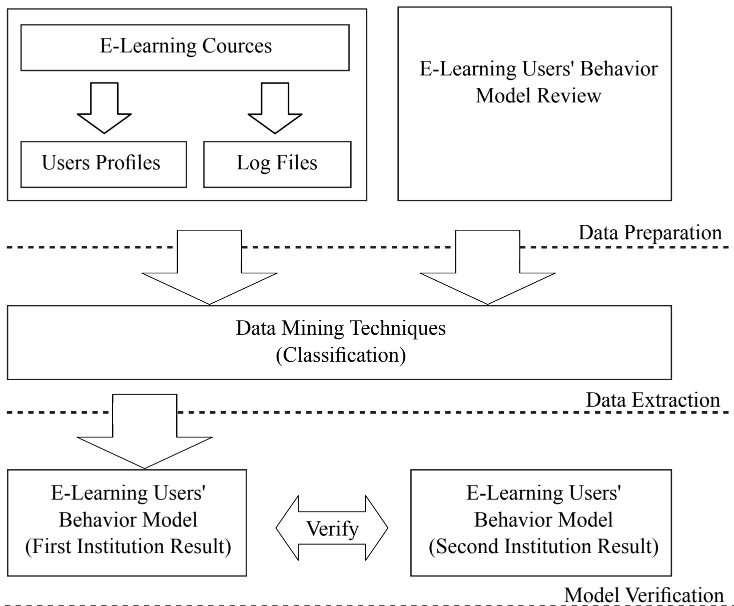

Figure 3. Proposed methodology.

DATA COLLECTION

Institutions Sampling

Basically, this study takes precedence over the different universities that have been using the same e-Learning system (Moodle). According to Henry (1990), the sampling could be chosen in very different conditions with the most similar/dissimilar cases sampling technique, as well as the "between-subjects experiments" as the type of experiment design identified that can be used for a large number of participants to compare the data set between learner groups on learner behaviour study (Chance, 2003). For this case, the web log of this research will be the large number of records. Hence, this research will be conducted by group studies. Levy (2003) identifies in his study six factors to be considered when planning online e-Learning programmes in higher education: vision and plans, curriculum, staff training and support, student services, student training and support, copyright and intellectual property. In reality, there are different educational policies between Malaysia and Thailand, which are related to these six factors (Yilmaz, 2010). Hence, two different universities from two different countries (Malaysia and Thailand) will be selected for the research sampling.

Course Sampling

Actually, the traditional courses and the e-Learning courses have all the activities from the beginning to the finishing point within a semester. The history usage of the and student results are kept in the vdatabase and web-log in the same session. Thereby, the web log collected from each course within one semester is sufficient for the study.

Accordingly, the purpose of this study is an approach to the appropriate users' behaviour model for learners' outcome prediction. The target rate of predicting performance is determined as at least 75 per cent (Witten & Frake, 2005) by using the SVM technique in the analysis process.

Each web-log from the selected courses should consist of three activities for behaviour classification processing; counting, timing and scoring as shown in Table 3 in order to get the proper outcome. Thus, the samples of this study are from every course taken at two different institutions which complete the processing components.

EVALUATION OF E-LEARNING USAGE BEHAVIOUR

For discussing the evaluation of the e-Learning users' behaviour, several interesting researches have been proposed. The behaviour evaluation displays three groups of attributes in the web-log. The three groups of attributes (count, time, score) are the dimensions for the user's behaviour evaluation that could classify all web-log attributes in these groups for the data analysis process. The attributes processing of the three groups are shown in Table 3.

Table 3 also shows the activities of the learner (web-log's records) comprising a number of activities, activities timing (period) and activities score. Thereby, processing these three groups processing could be useful as one of the e-Learning users' behaviour.

Table 3

Group of Web Log's Attributes Processing (Lingyan, et al., 2010)

Group of attributes processing	Attributes' activities
Count	▪ The number of learning resources (TotalCount) ▪ The number of asking questions (QuesCount) ▪ The number of answering questions (AnsCount) ▪ The number of sending posts (bbsSentCount) ▪ The number of replying posts (bbsAnsCount) ▪ The number of tests having been done (TestCount) ▪ The number of assignments (HomeworkCount)
Time	▪ The average time of learning resource (TotalTime)
Score	▪ The average score of the tests has been done (Test Score), which is divided into five levels: 'A' represents the score greater than or equal to 90 points, 'B' represents the score between 80 and 89 points, 'C' represents the score between 70 and 79 points, 'D' represents the score between 60 and 69 points, 'E' represents the score smaller than 60. ▪ The average score of assignment (HomeworkScore).

DATA MINING ON E-LEARNING DATA

In order to extract the information from the huge database in web-logs, data mining technique plays a crucial role. As mentioned in the study of Wen-Hai (2010), using the data mining technique to excavate client behaviour patterns from web-log files emphases the analyzing of client-behaviour pattern-recognition system and its application for obtaining client information conveniently and automatically.

The support vector machine (SVM) is one of the supervised learning methods that generates input-output mapping functions from a set of labelled training data. The mapping function can be either a classification function (i.e. the category of the input data) or a regression function (Vapnik & Cortes, 1995). SVM can reduce the computation cost for training data and give reasonable performance for pattern-classification handling {Zaki, 2002 #302}(Zaki, Deris, & Chin, 2002). For classification, nonlinear kernel functions are often used to transform input data to a high-dimensional feature space in which the input data become more separable compared to the original input space. Maximum-margin hyperplanes are then created. The model thus produced depends on only a subset of the training data near the class boundaries (Lipo, 2005). Thereby, the web log processing as shown in Table 3 and SVM for evaluation is also the method that could be used in this study.

The step of data analysis and evaluation could be used from the data mining processing steps. After that, the e-Learning system web-log and user profiles from the system databases are collected as data for the study. Finally, the data will be processed according to the steps shown in Figure 4.

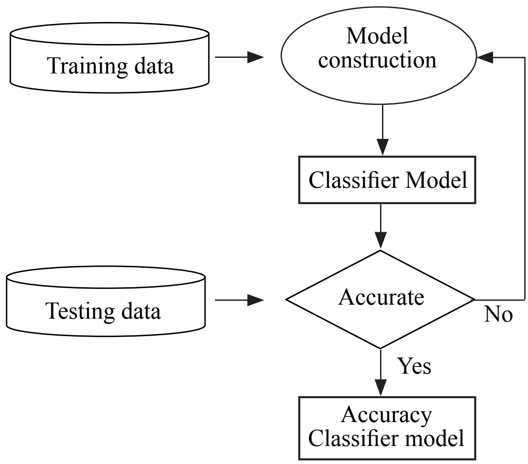

Figure 4. Accuracy classifier model finding.

The first step is data preparation. This step will involve three tasks, namely data cleaning, data selection, and data transformation. In data transformation, all attributes in the web-log will be classified into three groups; activities counting, activities timing (period), and activities score (see Table 3).

The second step is data extraction. This step will be processed with the classification technique. The Support Vector Machine (SVM) is the one of classification techniques that is suitable for learner behaviour analysis (Ribeiro & Cardoso, 2008) to develop a learner behaviour prediction model. This model will be used for predicting learners' grades that can affect learners' performance improvement. This process will divide the data obtained from the first step into two groups. Then a model will be constructed by using the SVM technique with training and test data until an accurate classification model is ensured.

A few techniques to the control data set number while doing the classification process such as the case slicing technique (CST) and also the 10-folds cross-validation. CST is supported with experiments on five datasets. The experiments have shown that using the CST indeed improves the high percentage of classification accuracy (Shiba, Sulaiman, Ahmad, & Mamat, 2003). The standard evaluation technique in the situation where only limited data is available is stratified through the 10-folds cross-validation (Witten & Frake, 2005). Thus, the partition of data for training and test setting will use the 10-fold cross-validation method, which has become the standard method in practical terms. Tests have also shown that the use of stratification improves results slightly. All data analysis is shown in Figure 4.

GENERALISE E-LEARNING USAGE BEHAVIOUR MODEL

According to the problem statement of this study, there is an unknown similar pattern from different user's behaviour models that need to be examined by following the flow chart as illustrated in Figure 5.

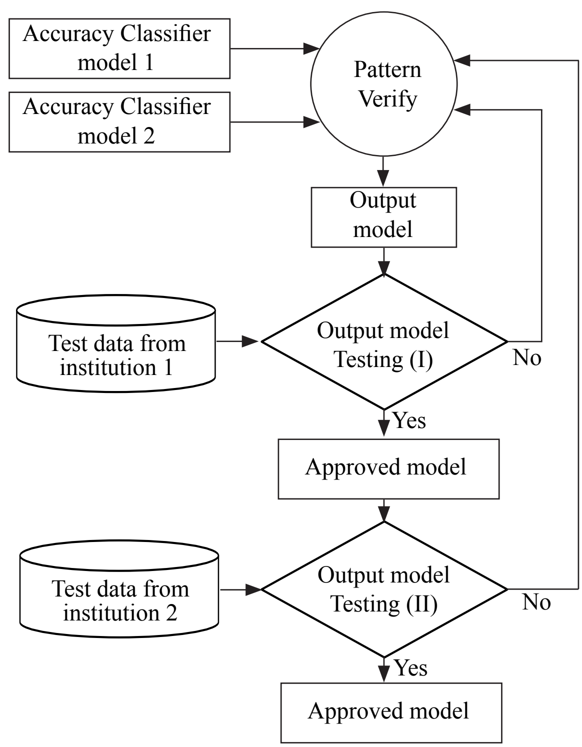

Figure 5. Model pattern verification.

As depicted in Figure 5, in the data extraction process, the results from both the institutions' accuracy classification models will proceed to verify the model pattern. Consequently, the new output model will come out from this step.

The model pattern-verification process is for adjusting the parameters and initial conditions of a model with another one in order to calibrate the new validity output model. Thereby, the output of this process is a pattern recording of the calibration of the two models.

The approved model (I) and the appropriate model as shown in Figure 5 are the outputs of the cross-validation process, which target that predicting performance will determine the success rate of at least 75 per cent (Witten & Frake, 2005).

In order to test the accuracy of the models, test data from institution 1 is availed to find out whether it can be approved or not. Once it is not approved as a right model, the model patterns verify process will be taken simultaneously. On the other hand, if it is approved, it will be employed for the second accuracy checking.

From the approved model (I), test data from institution 2 is used to find out whether it can be approved or not. If it is not approved as a right model, the model patterns verify process will be taken again. Once it is approved, the appropriate model will finally be discovered.

CONCLUSION

The abstruse learning problem is how learners achieve high learning outcomes. Such learning researches attempt to understand these causes. Previous learning models constructed by e-Learning web-log have explained their relevant determinants. These models aim to predict the learner status for learning direction change until learners find their best learning advantage. This concept is one solution to clear the doubt of how learners achieve high learning outcomes. The main goal of this research is to develop appropriate models to describe the e-Learning users' behaviour in order to be effective in educational development. Furthermore, an approach to unknown similar pattern of e-Learning usage behaviour models from different e-Learning systems is the important starting point to invent more appropriate general e-Learning usage behaviour models. From the weblog, the users' activities history in the e-Learning system is hidden inside the most important factors. This study suggests the new model could explain the relevance of the broader e-Learning users' behaviour. At the same time, this study presents the useful and universal model that is hidden in the system's history, which can contribute to other higher institutions in terms of the e-Learning system usage. Moreover, it is an advantage for the other higher institutions to use this model rather than create a new model which would incur time and cost for developing a new model of the e-Learning users' behavior. The pattern of two models verifying could be the base for further study in the users' behaviour function of a newer e-Learning system version.

REFERENCES

Chance, P. (2003). *The study of learning and behaviour learning & behaviour* (5th ed.). Belmont, CA: Phoenix Color Corp.

Chien Ming, C., Chao Yi, L., Te Yi, C., Bin Shyan, J., & Tsong Wuu, L. (2007). *Diagnosis of students' online learning portfolios*. Paper presented at the Frontiers In Education Conference - Global Engineering: Knowledge Without Borders, Opportunities Without Passports, FIE '07, 37th Annual, 10−13 Oct.

Chun Xia, Q., Hui Bao, C., Chang Yi, L., & Yue Xing, S. (2010). *Design an active e-learning system*. Paper presented at the 2nd International Conference on Education Technology and Computer (ICETC), 22−24 June.

Cotton, J. (1995). *The theory of learning*. London: Biddles, Guildford and King's Lynn.

Dai, S., & Zhang, P. (2008). *A data mining algorithm in distance learning*. Paper presented at the CSCWD 2008. 12th International Conference on Computer Supported Cooperative Work in Design, 16-18 April.

Graf, S., & List, B. (2005). A*n evaluation of open source e-learning platforms stressing adaptation issues*. Paper presented at the ICALT 2005. Fifth IEEE International Conference on Advanced Learning Technologies, 5−8 July.

Haythornthwaite, C., & Andrews, R. (2011). *E-learning theory and practice*. Singapore 048763: Sage Publications Asia-Pacific.

Henry, G. T. (1990). *Sample selection approaches practical sampling, 21*,17−32. California: Sage Publications.

Hsien Tang, L., Chih Hua, W., Chia Feng, L., & Shyan Ming, Y. (2009). *Annotating learning materials on Moodle LMS*. Paper presented at the ICCTD 09. International Conference on Computer Technology and Development, 13−15 Nov.

Kebin, H., Feimin, L., Ming, Z., Feng, W., & Xiaoshuang, X. (2008). *Design and implement on e-learning behaviour mine system*. Paper presented at the WGEC 08. Second International Conference on Genetic and Evolutionary Computing, 25−26 Sept.

Levy, S. (2003). Six factors to consider when planning online distance learning programs in higher education. *Online Journal of Distance Learning Administration*, *6* (1).

Lingyan, W., Jian, L., Lulu, D., & Pengkun, L. (2010). *E-Learning evaluation system based on data mining*. Paper presented at the 2nd International Symposium on Information Engineering and Electronic Commerce (IEEC), 23−25 July.

Lipo, W. (2005). *Support vector machines: Theory and applications,* 177. Berlin: Springer.

Min, J. (2005). *Development of an e-learning system for teaching machining technology*. Paper presented at the Proceedings of the 2005 International Conference on Active Media Technology, 19−21 May.

Moodle.org. (2011). *About moodle*. Retrieved from http://docs.moodle.org

O'Donohue, W., & Ferguson, K. E. (2001). *The psychology of B. F. Skinner*. United States of America: Sage Publication.

Rashty, D. (1999). *Traditional learning vs. eLearning*. Retrieved from http://www.rashty.com

Ribeiro, B., & Cardoso, A. (2008). *Evaluation system for e-learning with pattern mining tools*. Paper presented at the SMC 2008. IEEE International Conference on Systems, Man and Cybernetics 12−15 Oct.

Romero, C. B., Ventura, S., & Garcia, E. (2008). Data mining in course management systems: Moodle case study and tutorial. *Computers & Education*, *51*(1), 368−384.

Ruiz Reyes, N., Vera Candeas, P., Galan, S. G., Viciana, R., Canadas, F., & Reche, P. J. (2009, 22−24 June). *Comparing open-source e-learning platforms from adaptivity point of view*. Paper presented at the EAEEIE Annual Conference.

Sancristobal, E., Castro, M., Harward, J., Baley, P., DeLong, K., & Hardison, J. (2010). *Integration view of web labs and learning management systems*. Paper presented at the Education Engineering (EDUCON), IEEE, 14−16 April.

scorm.com. (2012). *Shareable content object reference model* (SCORM). Retrieved from http://scorm.com

Shiba, O. A. A., Sulaiman, M. N., Ahmad, F., & Mamat, A. (2003). An experimental evaluation of case slicing as a new classification technique. *Journal of Information and Communication Technology*, *2*, 105−117.

Vapnik, V., & Cortes, C. (1995). Support-vector networks. *Machine Learning*, *20*, 273−279.

Wen Hai, G. (2010, 11−14 July). *Research on client behaviour pattern recognition system based on Weblog mining*. Paper presented at the ICMLC 2010 International Conference on Machine Learning and Cybernetics.

Witten, I. H., & Frake, E. (2005). *Data mining: Practical machine learning tools and techniques* (2nd ed.). San Francisco, CA: Morgan Kaufmann.

Yilmaz, Y. (2010). *Higher education institutions in Thailand and Malaysia: Can they deliver?* Fiscal and Legislative Affairs Office of Revenue Analysis, DC.

Zaki, N. M., Deris, S., & Chin, K. K. (2002). Extending the decomposition algorithm for support vector machines training. *Journal of Information and Communication Technology*, *1*, 17−19.