

5th World Conference on Educational Sciences - WCES 2013

A Predictive Model to Evaluate Students' Cognitive Engagement in Online Learning

Nurbiha A Shukor^{a*}, Zaidatun Tasir^a, Henny Van der Meijden^b, Jamalludin Harun^a

^aFaculty of Education, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia

^bRadboud University, 6525 Nijmegen, Netherlands

Abstract

The expanding usage of online learning at all levels of education has drawn attention to the quality of online learning. In this study, online learning quality is evaluated through students' cognitive engagement which is reflected in their online written messages in discussions and their online participation. This study proposes the use of two types of data: students' participation, and written messages. Both types of data was collected and analyzed using the data mining technique to produce a predictive model that illustrates students' pathways while engaging in online learning cognitively. The findings of this study indicate that from 22 variables, only two were significant for students' online cognitive engagement; sharing information and posting high-level messages. The two variables led to the formation of three different pathways in the students' predictive model.

© 2013 The Authors. Published by Elsevier Ltd.

Selection and/or peer-review under responsibility of Academic World Education and Research Center.

Keywords: Online learning, cognitive engagement, content analysis, data mining

1. Introduction

Online educational spaces are a complex environment where students have to be highly responsible for their own learning (Nedelko, 2008). Online learning is often learner-centred and requires an amount of self-motivation (Nedelko, 2008; Smart & Chappel, 2006). However, one cannot deny the ubiquitous presence of online learning and the ability of online learning to overcome limitations such as geographical factors (Twigg, 2003). The expanding application of online learning in higher learning institutions has raised concerns about the quality of online learning (Chen, Guidry & Lambert, 2010). Researchers and educators have queried whether students have indeed 'learned' through online learning. If they did, to what extent did they learn? Researchers suggest that evaluation of the quality of online learning in order to ensure the appropriateness of online learning implementation is a necessity (Kwisnek, 2005).

The quality of online learning can be evaluated through observation of students' engagement in the online learning environment (Beer, Clark & Jones, 2010). Previous studies have reported that students' engagement has a significant influence on learning as it is related to academic performance (Burrows, 2010), knowledge acquisition (Chen et al., 2010), motivation (Scott & Walczak, 2009) and other learning benefits. Carini et al. (2006) investigated

* Corresponding Author: Nurbiha A Shukor. Tel.: +6017-3745760

E-mail address: nurbiha@utm.my

the extent of the association between students' engagement and academic performance. Academic performance was assessed by means of the RAND test, which is a test on critical thinking and problem-solving. They found that there is a positive but weak relationship between students' engagement and RAND test scores. They also found that students' engagement is positively correlated to students' grade point average (GPA). Morris et al. (2005) studied students' engagement in an online course through their log-in frequencies, duration of participation and thus drew relationships with their achievement.

However, these studies have been unable to explain the extent of students' learning online (Cotton & Yourke, 2006). Beer, Clark and Jones (2010) pointed out that these assessments were merely based on students' participation in online learning, which they claimed was not representative of students' online learning processes, and thus did not explain the overall quality of online learning. Zyngier (2008) further elaborated that low participation does not indicate disengagement. Participation does not necessarily result in learning and quantity is not similar to quality (Dennen & Paulus, 2005). In fact, Eskin and Ogan-Bekiroglu (2009) found that there is no significant relationship between the quantity of contributions and students' scientific understanding: students might respond frequently, but some of the responses reflect only low scientific understanding.

A more useful way of evaluating the quality of online learning is to assess the level of cognitive engagement of students working in an online environment to understand students' learning processes whereby online learning quality reflects a specific level at which students are cognitively engaged. Cognitive engagement is established when students exert an amount of mental effort to engage with the learning material (Richardson & Newby, 2006; Walker, Greene & Mansell, 2006). Research that explains cognitive engagement in online learning is plentiful (see works by Wysocki (2007) and Zhu (2006)) because cognitive engagement is a prerequisite for students' meaningful learning (Solis, 2008). Studies have indicated that students who are cognitively engaged are able to create new knowledge (Zhu, 2006) and they reach higher understanding in online discussions (Persell, 2004). Cognitive engagement is also found to be the predictor of achievement (Spanjers, 2007). In online learning, these abilities can be assessed by observing students' behaviour in their written messages (Van der Meijden, 2005; Zhu, 2006).

2. Research Background

2.1. Investigating Cognitive Engagement in Online Learning

Zhu (2006) explores cognitive engagement in four different settings of online learning. With the notion that cognitive engagement is not observable in online learning, the author initiated the exploration of "observing" cognitive engagement by analyzing students' behaviours of seeking, interpreting, analyzing and summarizing information, critiquing and reasoning through various options and arguments and making decisions in online discussions. Using her self-developed coding scheme, she found that students' levels of cognitive engagement in online learning discussion varied from high to low. However, Zhu found that there were many interrelated variables that caused students' cognitive engagements to vary and stated that her coding scheme was not investigated for validity and reliability.

Similarly, Wysocki (2007) was interested in investigating students' cognitive engagements in online learning. The approach in Wysocki's study was derived from previous works of Richardson and Newby (2006) and involved operationalizing cognitive engagement with respect to the types of learning strategies that the students employed in learning. Earlier, Richardson and Newby (2006) found that the "deep" and "achieving" strategies were significant for students with prior online learning experiences. Wysocki (2007) reported the opposite, that is, that prior online learning experiences had no effect on cognitive engagement. However, both Wysocki (2007) and Richardson and Newby (2006) used questionnaires to assess students' cognitive engagements. For the purpose of the present study, it is not necessary to discover more about this complex issue in greater depth.

Van der Meijden (2005) investigated cognitive engagement from the point of view of social knowledge construction, where students' elaboration while constructing knowledge was evaluated in online discussions. Students are categorized to be cognitively engaged at either a high or low level. Students at the low level are those who primarily did not elaborate on their statements when constructing knowledge, while students at high level explain their facts and ask questions that trigger other questions. Howard (1996) agreed with such measurement when he said that simple elaboration will not be as effective for learning as higher-level elaboration. Using

collaborative learning tasks, she found that students' levels of engagement varied according to the types of interactive media given.

The variety of results in online cognitive engagement and a few issues such as students being at the lower degree of cognitive engagement have raised the necessity of assessing cognitive engagement, particularly in an online learning context to a greater extent.

2.2. A predictive model to explain students' cognitive engagement in online learning

Analyzing students' online written messages often reveals knowledge with regard to the interaction patterns of the students, which online behaviour appears the most frequently, and why a specific behaviour is most likely to occur (McLoughlin & Luca, 2000; Zhu, 2006). However, such investigations do not uncover the pathway of how higher-level cognitive engagement can be achieved. That is, to be able to reach higher-level cognitive engagement in online learning, which elements should co-exist? Macfadyen and Dawson (2010) found that the online learning variables that can predict students' better future performance in tests, using a predictive model, are: the number of discussion messages posted, number of assessments finished, and number of mail messages sent. Similarly, Hung and Zhang (2008) found that students who were able to achieve final grades of more than 80 (percentage) were associated with variables such as frequency of accessing course materials, number of bulletin board messages read, and frequency of accessing course materials. These studies explained students' better future performance in tests with respect to their participation in online learning.

For determining online learning quality through cognitive engagement, a predictive model should be constructed in order to assist educators to understand which online variables can predict higher-level cognitive engagement and help to explain the pathway that the students should take to achieve a higher level. Using the knowledge from this investigation, educators can be aware of the specific aspects that need more attention for online learning quality, so that improvement and interventions in online learning instructions can be made. By analyzing both the students' online participation and their level of cognitive engagement, this study reports on an initial learning set for a student cognitive engagement predictive model. The resulting learning set will be a useful guide for teachers to propose early interventions for students' better cognitive engagement in online learning. Thus, the following research questions were formulated:

- (1) What is the students' level of cognitive engagement in an online learning environment?
- (2) Is it possible to create a model that predicts future cognitive engagement in an online learning setting?

3. Research Methodology

3.1. Participants and procedures

The participants of this study were 20 undergraduate students who enrolled in a course on web-based multimedia development at the Universiti Teknologi Malaysia. There were 5 males and 15 females. They were selected randomly out of 80 students enrolled in this course. Samples in this study were required to complete five problem-solving tasks through online discussions related to the problems that they faced while developing a functional educational website in groups of 4 or 5 students. They also used online learning to access course materials (a content page, web links, self-reports), to download notes and to ask questions to the instructor. The online learning environment was developed in a Learning Management System (LMS), Moodle. Students' participation in online learning was rewarded 20% of their overall achievement for the subject.

3.2. Analysis of data

This study compiled data from both the LMS and students' online written messages through online discussions. Thus, this study adapted the integrated analytical model by Shukor et al. (2012) for analyzing both types of data as in Figure 1.

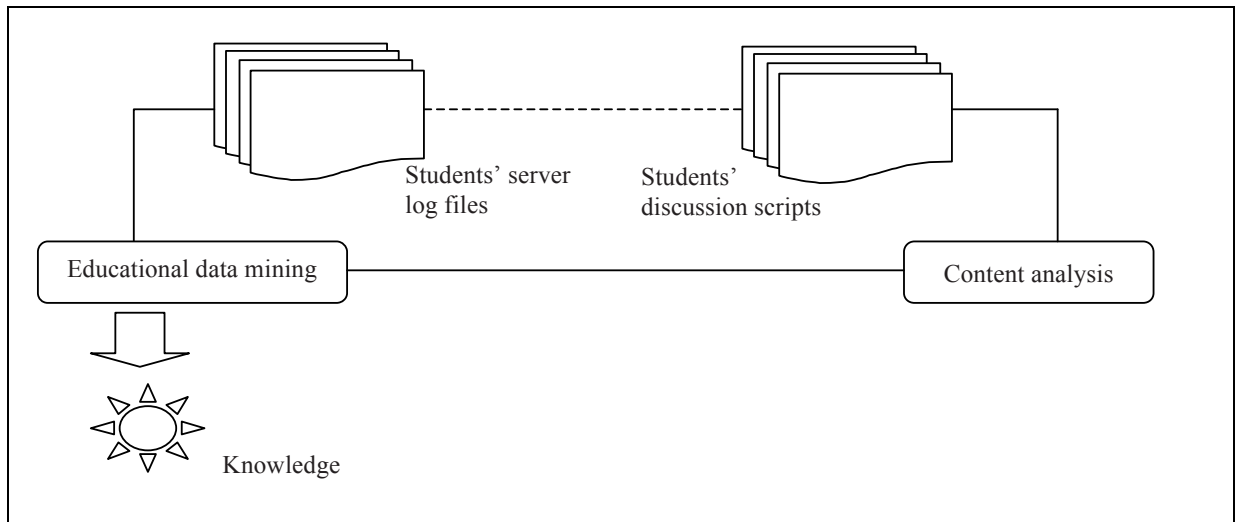


Figure 1. The integrated analytical model for analyzing students' online learning processes (Shukor et al., 2012).

3.2.1. Analysis of students' written messages

Students' written messages while solving the problem-solving tasks were collected and divided into segments and categorized by two coders. The inter-rater reliability was found to be 0.745 which Fleiss (1981) concluded as good. Using the "meaning" as the unit of analysis, 430 segments were calculated from a total of 415 messages. These segments were then coded according to the cognitive engagement coding scheme proposed by Van der Meijden (2005). To analyze students' interactions online, she developed a coding scheme with three dimensions: the cognitive, regulative and affective dimension. The cognitive dimension refers to the thinking activities that students use to process learning content and attain learning goals. The types of learning content can be facts, concepts, formulas, reasoning, arguments, definitions and conclusions. She made a distinction between high-level and low-level cognitive elaboration. High-level elaboration encompassed five of the categories from the cognitive dimension of the coding scheme, namely: comprehension questions asking for elaboration (CHV2), answers with elaboration (CHG2), presentation of new ideas with further elaboration (CI2), acceptance with further elaboration (ACCEPT+), and rejection with further elaboration (REJECT+). Low-level elaboration encompassed the other eight categories from the cognitive dimension of the coding scheme: factual questions (CHV1), verification questions (CHVER), answers only (CHG1), presentation of new ideas without further elaboration (CI1), references to previously discussed ideas (CIT), summarization (CIE), acceptance without further elaboration (ACCEPT-), and rejection without further elaboration (REJECT-).

In the present study, only the cognitive dimension was used (13 categories) as presented in Table 1. Based on the categories of Van der Meijden (2005), students' individual cognitive engagement was calculated to be categorized into high (H), high-low (HL) or low (L) level of cognitive engagement. This was done by comparing the percentage of their high-level cognitive contributions with the low-level cognitive contributions. The results were stored in an Excel spreadsheet and later compiled with the dataset from the LMS database.

Table 1. Cognitive dimensions for investigating cognitive engagement

Cognitive: Asking Questions		Examples of Use
CHV 1	Asking questions that do not require an explanation (facts or simple questions)	Has the problem been solved? How many types of images are there?
*CHV 2	Asking questions that require an explanation (comprehension or elaboration)	You have explained all the units for developing the website, but which one is preferable and why? Do you have any idea about solving the problem?

CHVER	Verification or asking for agreement	Can we do anything to fix this? Is it true? Am I explaining correctly?
Cognitive: Giving Answers		
CHG 1	Answering without explanation	There are 3 types of images. The problem has been solved. .jpeg is different than .png image.
*CHG 2	Answering with explanation (using arguments or by asking a counter-question)	It means that not all computer resolution is the same because... The information shows that...
Cognitive: Giving Information		
CI 1	Giving information (an idea or thought) without elaboration	I paste the information from the internet as presented below... From what I see, both images look the same.
*CI 2	Giving information (an idea or thought) with elaboration	I guess the alternative way to solve this is by... From the example that I obtained from the internet below, they say that... Some of the discussion said so because...
CIT	Referring to earlier remark/information	We often have the same problem... This problem has occurred to me before... Based on Aishah's explanation...
CIE	Evaluating the content (summarizing/concluding)	So, the verdict is... We can conclude that...
ACCEPT-	Accepting contribution of another participant without elaboration	I agree. You might be right.
*ACCEPT+	Accepting contribution of another participant with elaboration	I agree with you because... Aishah is right because...
REJECT-	Not accepting contribution of another participant without elaboration	I don't think that is the cause of the problem. I don't think that is right.
*REJECT+	Not accepting contribution of another participant with elaboration	That might not be the problem because... I disagree with you because...
* indicates high-level cognitive engagement		

3.2.2. Analysis of students' online participation based on LMS data

Students' data on their participation in online learning were retrieved from the LMS database. Activities such as frequency of logging-in, number of posted messages, frequencies of viewing messages, discussions, and accessing course materials were extracted from the data. Next, the data were exported to an Excel spreadsheet to merge with the codes of cognitive engagement in the discussion scripts. The complete dataset was used twice: the data was imported into SPSS for further statistical analysis, and was also imported into WEKA for data mining purposes. Data mining of the complete dataset resulted in the construction of a predictive model for students' cognitive engagement in online learning. The overall variables involved are presented in Table 2.

Table 2. Variables involved in developing the cognitive engagement predictive model

Variable	Descriptions
LoginFre	Total frequency of LMS logins
ResView	Total frequency of accessing course materials
NoPosting	Total number of discussion board messages posted
LevCE	Individual level of cognitive engagement (H/ H-L/ L)
NoCHV2	Total number of messages of CHV2 level posted
NoCHG2	Total number of messages of CHG2 level posted
NoCI2	Total number of messages of CI2 level posted
NoACCEPT+	Total number of messages of ACCEPT+ level posted
NoREJECT+	Total number of messages of NACCEPT+ level posted
NoCHV1	Total number of messages of CHV1 level posted
NoCHVER	Total number of messages of CHVER level posted
NoCHG1	Total number of messages of CHG1 level posted
NoCI1	Total number of messages of CI1 level posted
NoCIT	Total number of messages of CIT level posted
NoCIE	Total number of messages of CIE level posted
NoACCEPT-	Total number of messages of ACCEPT- level posted

NoREJECT-	Total number of messages of NACCEPT level posted
NoHCog	Total number of high-level cognitive contributions
NoLCog	Total number of low-level cognitive contributions
NoCog	Total number of cognitive contributions

4. Results and Findings

4.1. Students' level of cognitive engagement in online learning

Table 3 shows the descriptive statistics of students' activities in online learning which includes their participation by adding posts, viewing discussions, logging-in, and accessing resources (web links, notes). With respect to problem-solving activities through online discussions, the students' written messages were coded and categorized into low-level or high-level cognitive contributions. It was found that students' levels of cognitive engagement were considerably low. The mean for high-level cognitive contributions was lower than the low-level cognitive contributions. By comparing the percentages of both high-level and low-level cognitive contributions with the respective means, 8 students were categorized as having a high level of cognitive engagement (H), 7 students as having a high-low level of cognitive engagement (HL) and 5 students were categorized as having a low level of cognitive engagement (L). This categorization signifies that students in the H category were able (to a greater degree) to elaborate information, ask questions that required further explanations, or critique information with explanations compared to students in the other categories.

Table 3. Descriptive statistics of students' online participation and cognitive engagement in online learning

Online Activity	Frequency	Percentages	Mean
Log-in	1158	19.60	57.90
Resource View	805	13.62	40.25
Discussion View	3372	57.07	168.60
Add Post	574	9.71	28.70
Low-level cognitive engagement	180	61.64	9.0
High-level cognitive engagement	112	38.36	5.6

The data retrieved from the LMS database show that the most frequent activity was viewing discussions (57.07%) (see Table 3). It can be observed that the frequency of logging-in was less than viewing discussions (19.60%). It signifies that every time the students logged in, they viewed discussions repeatedly. The high percentages were expected because students were required to solve several problem-solving tasks through online discussions. Relating both students' online participation and their levels of cognitive engagement, a high frequency of participation does not necessarily ensure a high level of cognitive engagement.

4.2. Variables involved in the students predictive model in online learning

To develop a predictive model, both sets of data from the content analysis and the LMS were combined and analyzed using the data mining technique. The predictive model is presented in Figure 2. As shown in Figure 2, from the total 22 variables listed for investigation, only 2 variables emerged: the NoHcog and CI1. The predictive model has high Kappa reliability of 0.845 which suggests that it is a model with an almost perfect agreement and that the obtained results are not due to chance (Viera, Joanne & Garrett, 2005). The emergence of the NoHcog code was expected in this study because the NoHcog code is the total of high-level cognitive contributions including from the codes CI2, CHV2, CHG2, ACCEPT+ and REJECT+.

The predictive model tells us that having more than four messages of either of these types will lead to the students achieving a high level of cognitive engagement. On the other hand, students who posted more than six messages at the level of sharing information only (that is, no elaboration was provided, CI1), were more likely to reach a low level of cognitive engagement. Seven students, who were in the category of HL, followed a similar

pathway as the H students but since they posted less than four messages at the high level, it caused them to fall into this category.

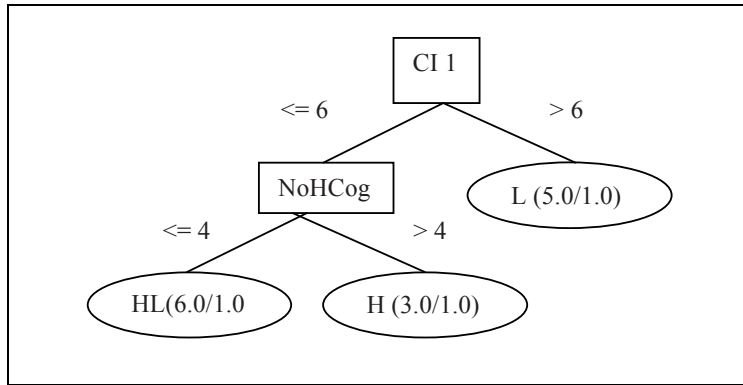


Figure 2. Predictive model of students’ cognitive engagement in online learning.

In sum, there were a total of three pathways in order to achieve either the H, H-L or L category. The pathways are simplified in Table 4. The summary of the pathways in Table 4 tells us that all students from the H, HL and L category took similar pathways to reach their respective levels. Students from the H and HL categories were found to take a similar pathway (CI1 and NoHcog) to reach their respective levels. Differences between the two levels were due to the frequency of Hcog codes that they contributed (either more than four or less than four).

Table 4. Summary of students’ pathways for cognitive engagement in online learning

Levels of Cognitive Engagement	Pathway
High-level cognitive engagement (H)	CI 1 (<= 6) – NoHcog (> 4)
High-low level cognitive engagement (H-L)	CI 1 (<= 6) – NoHcog (<= 4)
Low-level cognitive engagement (L)	CI 1 (> 6)

5. Discussions

Two questions were posed in this research: What is students’ level of cognitive engagement in an online learning environment? Is it possible to create a model that predicts future cognitive engagement in an online learning setting?

In this study, the first research question addressed the level of cognitive engagement. As shown in Table 3, a lower mean for high-level cognitive contributions as compared to low-level cognitive contributions was observed. These results are similar to those obtained by previous researchers such as Chang and Sung (2008), Hou and Wu (2011), Hou, McLoughlin and Luca (2000), Van der Meijden (2005) and Zhu (2006). They found that students struggled to achieve higher-level cognitive interactions while constructing knowledge such as applying newly co-constructed knowledge. Most of the students were able to compare and share information but were seldom able to negotiate the meanings and discover new knowledge (Hou, Chang & Sung, 2008; Hou & Wu, 2011).

In the present study, students tended to copy information directly from the internet (such messages were coded as CI1) while hoping for their peers to comment on them. An example is shown below:

Student 16: *Oh my friends, lets check here: (information found in the internet)*

Many people ask “Why my web design is different when using Mozilla and IE?” How do I get best web design that is displayed on Mozilla and Internet Explorer can be same? What HTML validation function is? Standardization is applied by the W3C .. (CI1).

When students tended to ‘copy and paste’ the information from the internet, they spent less effort in constructing their own sentences for explaining. According to Dornisch et al. (2011), this is not surprising, particularly when

students had less prior knowledge about the task and when the task introduced them to new concepts for learning. McLoughlin and Luca (2000) found that students with lower levels of prior knowledge tended to discuss on a more sharing information level (CI1). From this point of view, the availability of the enormous amount of information on the internet might disadvantage students' online learning. Directly copying information without explaining concepts discourages deep thinking and the ability to construct information in their own words, which results in poor quality online learning experiences.

On the other hand, students at the high level (H) and medium level (HL) of cognitive engagement were associated with the variable NoHcog. Students who were able to reach a high level of cognitive engagement were self-regulating as shown in the study by Corno and Mandinach (1983). At this level, students were able to process information by being alert and selective and by connecting, planning and monitoring their learning process (Corno & Mandinach, 1983). An example of students' discussion script coded at the high level of cognitive engagement is shown below:

Student 11: *Now, if we talk about bit rate, here is the info.*

"The bitrate is simply a measure of ..."

You might also wonder why I haven't said anything about file format or video format. If you encode some video at 786 kbps, your ... (CI2).

As shown in the above script, Student 11 shared the information that he found on the internet about 'bitrate'. He later explained what he understood from the information that he found to the other group members (coded CI2). Dornisch et al. (2011) shared a similar insight when they mentioned that students who were able to elaborate on statements had the advantage of increased understanding of the learning content. While elaborating, students relate prior knowledge to the context of learning and this promotes information processing at a deep level (Dornisch et al., 2011; Nussbaum, 2008). In turn, activating the prior knowledge through elaborating and explaining also promotes critical thinking and reflections (Rizopoulos & McCarthy, 2009).

Some of the students in the L category had high frequency of viewing discussions and posted more messages than the rest but only reached a low level of cognitive engagement. Such findings strengthen the earlier expectation that students' online learning has to be evaluated from both quality and quantitative aspects. It suggests that the students might spend more time in reading the discussion threads rather than responding to the discussions. However, as emphasized in this study, each message that the students posted might be at a different quality and thus the frequency does not matter. In a study by Macfadyen and Dawson (2010), the number of posted messages was found to predict students' success. However, it is important to note that a greater level of participation does not necessarily result in higher academic performance. Nevertheless, it is evident that students who interact less tend to fail their course (Davies & Graff, 2005).

The second research question of this study addressed the possibility of developing a predictive model and identifying the relevant variables. The predictive model proposed in this study proved to be reliable. The learning set showed that only certain behaviors can contribute to students' cognitive engagement in online learning. The emergence of NoHcog was expected in this study; in contrast, the emergence of the CI1 code was less expected. However, the predictive model suggests that this code emerged because it led to a low level of cognitive engagement. CI1 falls within the low level of cognitive engagement indicators (see Table 1). Hence, due to less elaboration while sharing information with peers, students were unable to reach a high level of cognitive engagement. Posting too many messages of this type will disadvantage students' learning, because they might lead to low level of cognitive engagement.

The predictive model learning set constructed in this study suggests the significance of only certain variables and demonstrates that other variables (such as Login, NoPost, ResView) emerged less frequently and thus these variables were not predicted. Consequently, it also suggests that the other variables were not associated with students' achieving a certain level of cognitive engagement in online learning except CI1 and NoHcog.

This contradiction is explained, for example, from the results by Hung and Zhang (2008) who found that log-in frequency, number of messages read and number of messages posted predicted students' future performance. In a similar prediction, Macfadyen and Dawson (2010) found that students' future performance was associated with the

number of discussion messages posted, number of assessments finished and number of mail messages sent. However, these results were predicted with respect to academic achievement while in this study, the major concern is on predicting the quality of learning measured through students' cognitive engagement. Additionally, Macfadyen and Dawson (2010) agreed that they did not consider the quality aspects of online learning processes.

6. Conclusion

The purpose of this study was to evaluate the quality of students' online learning by assessing both their online discussion scripts and online participation activities. By combining content analysis and data mining, students' levels of cognitive engagement were explored. Generally, students were struggling to contribute messages at a high level of cognitive engagement. However, more students were categorized into having a high level of cognitive engagement compared to the other categories. When the pathways of these categories were investigated, only the CII and NoHcog variables were found to be associated with their levels of cognitive engagement. Further examination also showed that the students followed similar pathways for reaching their respective category (one pathway for H, HL and L, respectively). From this point of view, this study suggests that for better future cognitive engagement in online learning, the two variables should be monitored and supported in order to lead students to high-level cognitive engagement.

As described earlier, this study was limited by the provision of a learning set for which samples were small. Notwithstanding, it was reliable enough to construct a predictive model learning set. In future research, the model should be replicated with larger samples involved, emphasizing the variables predicted in our learning set. Additionally, although the predictive model was found to be reliable, a statistical relationship between the predicted variables needs to be established.

The results of the present study might inspire other researchers to combine both techniques (content analysis and data mining) to further evaluate the quality of online learning by producing a valid predictive model based on the learning set provided in this study. The results of this study will help us to make students' learning processes more transparent because the underlying processes that led to the students' specific categories can be found. It will also give teachers the opportunity to provide early intervention and guidelines for designing online learning activities.

Acknowledgements

The authors would like to thank the Universiti Teknologi Malaysia (UTM) and Ministry of Higher Education (MoHE) Malaysia for their support in making this project possible. This work was supported by the Research University Grant [Q.J130000.2616.00J83] initiated by UTM and MoHE.

References

- Beer, C. Clark, K., & Jones, D. (2010). Indicators of engagement. In C.H. Steel, M.J. Keppell, P. Gerbic & S. Housego (Eds.), *Curriculum, technology & transformation for an unknown future* (75-86). Sydney: Ascilite.
- Blumenfeld, C. P., Kempler, M. T., & Krajcik, S. J. (2006). Motivation and Cognitive Engagement in Learning Environments. In Sawyer, R. K (Ed.), *Cambridge Handbook of Learning Sciences*, 475- 488.
- Burrows, Peter L. (2010). *An examination of the relationship among affective, cognitive, behavioral, and academic factors of student engagement of 9th grade students*. Thesis. University of Oregon.
- Carini, R. M., Kuh, G. D. & Klein, S. P. (2006). Student engagement and student learning: Testing the linkages. *Research in Higher Education*, 47(1), 1-31.
- Chen, P. D., Lambert, A. D., & Guidry, K. R. (2010). Engaging online learners: The impact of web-based learning technology on student engagement. *Computers & Education*, 54(4), 1222-1232.
- Corno, L., & Mandinach, E. B. (1983). The Role of Cognitive Engagement in Classroom Learning and Motivation. *Educational Psychology*. 18(2), 88-108.
- Cotton, D. & Yorke, J. (2006). Analyzing online discussions: What are the students learning? In *Proceedings of the 23rd Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education: "Who's learning? Whose technology?"* December, 2006, Sydney, Australia.
- Davies, J. and Graff, M. (2005). Performance in e-learning: Online participation and student grades. *British Journal of Educational Technology*, 36 (4), 657-663.

- Dennen, V. P. & Paulus, T. M. (2005). Researching “collaborative knowledge building” in formal distance learning environments. *Proceedings of CSCL 2005*. Taipei: International Society of the Learning Sciences.
- Dornisch, M., Sperling, R. A. & Zeruth, J. A. (2011). The effect of levels of elaboration on learners’ strategic processing of text. *Instructional Science*, 39(1), 1-26.
- Eskin and Ogan-Bekiroglu, H. (2009). Investigation of a pattern between students’ engagement and their science content knowledge: A case study. *Eurasia Journal of Mathematics, Science & Technology Education*, 5(1), 63–70.
- Fleiss, J. L. (1981). *Statistical methods for rates and proportions*. (2nd ed). New York: John Wiley.
- Greene, A. B., Miller, B. R., Crowson, H. M., Duke, L. B. & Akey, L. K. (2004). Predicting High-school students’ cognitive engagement and achievement: Contributions of classroom perceptions and motivation. *Contemporary Educational Psychology*, 29, 462-482.
- Hou, H.-T., Chang, K.-E., & Sung, Y.-T. (2008). Analysis of Problem-Solving-Based Online Asynchronous Discussion Pattern. *Educational Technology & Society*, 11 (1), 17-28.
- Hou, H., & Wu, S. (2011). Analyzing the social knowledge construction behavioural patterns of an online synchronous collaborative discussion instructional activity using an instant messaging tool: A case study. *Computers & Education*, 57(2), 1459-1468.
- Howard, B. C. (1996). Cognitive Engagement in Cooperative Learning. Paper presented at the *Annual Meeting of the Eastern Educational Research Association*. Boston: MA.
- Hung, J.-L., & Zhang, K. (2008). Revealing Online Learning Behaviours and Activity Patterns and Making Predictions with Data Mining Techniques in Online Teaching. *MERLOT Journal of Online Learning and Teaching*, 4(4), 426-437.
- Kong, Q., Wong, N., & Lam, C. (2003). Student engagement in mathematics: Development of instrument and validation of construct. *Mathematics Education Research Journal*, 15(1), 4-21.
- Kwisnek, F.V. (2005). Assessing the Effectiveness of E-Learning. In Darbyshire, P. *Instructional Technologies: Cognitive Aspects of Online Programs*. USA. 192- 220.
- Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an early warning system for educators: A proof of concept. *Computers & Education*, 54(2), 588-599.
- McLoughlin, C. & Luca, J. (2000). Cognitive Engagement and Higher Order Thinking through Computer Conferencing: We Know Why but Do We Know How?. In A. Herrmann and M.M. Kulski (Eds), *Flexible Futures in Tertiary Teaching. Proceedings of the 9th Annual Teaching Learning Forum*, Perth: Curtin University of Technology.
- Morris, L. V., Finnegan, C., & Wu, S. (2005). Tracking student behavior, persistence, and achievement in online courses. *Internet and Higher Education*, 8, 221-231.
- Nedelko, Z. (2008). Participants’ Characteristics for E-Learning. *E-Leader Conference*, Krakow.
- Nussbaum, E. M. (2008). Collaborative discourse, argumentation, and learning: Preface and literature review. *Contemporary Educational Psychology*, 33(3), 345–359.
- Persell, C.H. (2004). Using Focused Web-based Discussions to Enhance Student Engagement and Deep Understanding. *Teaching Sociology*, 32(1), 61-78.
- Richardson, J. C., & Newby, T. (2006). The Role of Students’ Cognitive Engagement in Online Learning. *American Journal of Distance Education*. 20(1), 23-37.
- Rizopoulos, L. A. & McCarthy, P. (2009). Using online threaded discussions: Best practices for the digital learner. *Journal of Educational Technology Systems*, 37(4), 373-383.
- Scott, E. J. & Walczak, S. (2009). Cognitive Engagement with a multimedia ERP tool: Assessing computer self-efficacy and technology acceptance. *Information & Management*, 46, 221-232.
- Shukor, N. A., Tasir, Z., Van der Meijden, H. & Harun, J. (2012). An integrated analytical model to gain knowledge from students’ online discussions. Paper presented at *International educational Technology Conference*, Taipei.
- Smart, K.L. and Chappel, J.J.(2006). Students’ Perceptions of Online Learning: A Comparative Study. *Journal of Information Technology Education*, 5, 201-219.
- Solis, A. (2008). Teaching for Cognitive Engagement: Materializing the Promise of Sheltered Instruction. IDRA Newsletter. *School Engagement: Potential of the Concept*, State of the Evidence.
- Spanjers, D. M. (2007). *Cognitive engagement as a predictor of achievement*. Dissertation. University of Minnesota.
- Twigg, C. A. (2003). New Models for Online Learning. *EDUCAUSE Review*. September/October 2003. 29- 38.
- Van der Meijden, H. (2005). *Knowledge Construction through CSCL: Student Elaborations in synchronous, asynchronous, and three-dimensional learning environments*. Doctoral Thesis. Nijmegen: Radboud University.
- Walker, O. C., Greene, A. B. & Mansell, A. R. (2006). Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement. *Learning and Individual Differences*, 16, 1-12.
- Wysocki, C.D. (2007). *A Study of Cognitive Engagement in Online Learning*. Dissertation, Washington State University, USA.
- Zhu, E. (2006). Interaction and cognitive engagement: An analysis of four asynchronous online discussions. *Instructional Science*, 34(6), 451-480.
- Zyngier, D. (2008). (Re) Conceptualising student engagement doing education not doing time. *Teaching and Teacher Education: an International Journal of Research and Studies*. 24 (7) 1765-1776.