DIFFERENCES IN LEARNING MANAGEMENT SYSTEM USE BY TEACHERS WHO PARTICIPATE IN TRAINING

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ABSTRACT

University investment in online learning infrastructure is substantial and a significant part of this is the learning management system (LMS). In addition to the investment cost, there are the costs associated with training for staff. Typically, the effectiveness of LMS training is measured with surveys asking about participants' subjective views about the training, such as usefulness, satisfaction and applicability to their teaching. However, participants' post-training behaviour, which can be obtained from LMS usage logs, can provide objective evidence of the effect of training on teachers' LMS use. Analysis of LMS logs reported in this paper show that both teachers who have received LMS training and their students are more active in their online courses compared to those who have not. However, the increased activity is only in relation to content. This preliminary analysis of usage data in conjunction with training information suggests a positive effect of training, although in this case mainly in the use of content by students.

Keywords: Learning Management System, Teacher Training, Learning Analytics.

INTRODUCTION

Investment by universities in providing eLearning training to staff is substantial, particularly in relation to use of their institutional learning management system (LMS). However, training effectiveness is usually measured by asking participants to provide their views about the training, such as whether they feel it was effective and whether they were satisfied with the training. While these views are useful, they are subjective measures of training effectiveness. Participants' behaviour post-trainingis an objective method for evaluating training effectiveness, a measure of which can be obtained from LMS tracking logs. In this paper we report on preliminary analysis of these logs,to examine how activity levels in LMS usage by teachers and their students differ depending on whether the teacher has undergone LMS training or not and whether use of the LMS differs depending on the class size. Analysis of LMS data has been reported in a number of studies (e.g., Jurado, Pettersson, Gomez,& Scheja, 2014; Lam, Lo, & Lee, 2010; Lam, Keing, McNaught, & Cheung, 2006; Morris, Finnegan,& Wu, 2005; Phillips, 2006; Romero, Ventura,& García, 2008). However, with advances in learning analytics, greater attention is being paid to analysing large data sets to understand learner behavior and optimising learning outcomes for students (Reyes, 2015), with LMS logs being a logical source of data for analysis. Typically, the focus of this analysis is to understand learner behaviour in the LMS and its impact on learning outcomes for students. However, learning analytics can also assist institutions in gaining valuable insights to inform strategic decision making, particularly in regard to resource allocation (Lam et al., 2006; Macfadyen & Dawson, 2012). In this paper we report on the application of learning analytics to Blackboard usage logs to understand the effects of LMS training on teachers' and students' activity in online courses. Our aim is to understand if the online behaviour of participants who have attended training or their students is different to that of teachers who have not attended training and, if so, in what way is it different and what implications this has.

LITERATURE REVIEW

LMS Usage Logs

Phillips (2006) was amongst the earliest to report that the institutional LMS at several universities was being used mainly for providing students with content and information, a finding that has been replicated in other studies (e.g., Jurado et al., 2014). To assist in understanding how teachers use the LMS, classification systems based on tool usage have been developed and used to analyse LMS usage data. For example, Montenegro-Marin, Cueva-Lovell, Sanjuan and Nuñez-Valdez (2011) developed an ontology of modules common in learning management system platforms, which included *tools*, consisting of administration, communications, course, curricula design, and productivity, and *users*. Another classification system for LMS features was developed by Jurado and colleagues (2014) where tools are categorised according to purpose: for distribution (e.g., contents page, URL, documents, etc.), communication (e.g., mail, calendar, announcements), interaction (e.g., discussion areas, assignments, surveys, quizzes) or course management (e.g., gradebook, student tracking). Their work has shown that tools for distribution are used far more than tools for communication or interaction, which is consistent with Phillips' finding from eight years earlier.

Useful information is obtained from analysis of usage data at this level. For example, students' final grades have been shown to correlate with counts of tool usage (Macfayden& Dawson, 2010; Morris et al., 2005). Morris and colleagues (2005) studied student behaviour, persistence and achievement in online courses and showed via regression analysis that counts of tool use are significantly correlated with final grades. In addition, students who successfully completed the course engaged with online learning activities with greater frequency and for longer durations than did unsuccessful students who eventually withdrew. Similarly, Walsh (2015) found a statistically significant, but weak, positive correlation between students' overall results and number of logins and frequency of accessing content, which he stated suggested that frequency of login and hit activity in the LMS may be an effective predictor of performance. He also noted that his finding was consist with that of others such as Smith, Lange and Huston (2012) and Whitmer et al (2012) who found similar correlations. For this study we compared LMS usage data for courses taught by teachers who have undertaken LMS-related training offered by the University with those of teachers who have not. In doing so, we hoped to provide insight into the effect of training on LMS use and obtain important evidence of the effectiveness of training for promoting LMS usage by both students and staff to inform future training practice at our institution. The focus on actual behaviour is an important aspect of this approach - research by Saks and Burke (2012)

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showed that self-report transfer of training is significantly predicted by training evaluation, but only if the evaluation includes analysis of behaviour and outcomes. In particular, they found that organisations report higher rates of transfer of training where more frequent evaluation of training in terms of behaviour and results is conducted. In terms of evaluating LMS training effectiveness, usage data can be used as measures of behaviour and results and this represents a new approach to assessing training outcomes. This is important, because, as Weaver (2006) notes, training of staff to support them in using the LMS needs to continually evolve to promote discussion and adoption of best practice, to cater to different staff requirements and to keep up with changes in the LMS itself as well as changes to other elearning tools. Understanding how eLearning training, particularly in relation to an institutional LMS, impacts teaching practice and use of the LMS is important for assessing the effectiveness of training and staff development. As Picciano (2014) notes, data-driven decision making relies on an appropriate model and valid data. For this study it was expected that if LMS training is effective, then teachers who undertake training should be more active in their LMS use, one measure of which is click counts for various tools. We also expected that if teachers are more active in the LMS, then so too should their students be.

METHODOLOGY

The LMS used at our university is Blackboard (www.blackboard.com). We have spent a significant amount of time conducting experiments to test the accuracy of the logs generated by use of the LMS to understand what variables in the logs represent. All analyses have been conducted using an isolated system - under the university's current data security policy, to avoid the possibility of degradation of performance of the live system, direct access to the live LMS database (DB) is not permitted. Additionally, there are over 200,000 activity logs recorded in the live database every second. To overcome this limitation, an LMS testing server (LMS Data Hub) maintained by our department was developed for this study, which served as a data repository for all data used in this study. Using LMS Data Hub, a methodology for analysing the activities of both teachers and students from the Blackboard LMS users action log (called the Activity Accumulator Table) was developed. This methodology was used to transform the extracted data into a format that could be analysed to produce custom-made indicators and reports.

Three semesters (i.e., one academic year) of retrospective data from the university's LMS were obtained for analysis. In addition, data from the central training participation information system were used to identify staff who had undertaken LMS-related training conducted by the University in the last four years and those who had not. The retrospective training data and the activity logs recorded in LMS database were copied to a new database in the LMS Data Hub, which itself was built and protected under University IT Private Cloud Infrastructure. Inside the LMS database, information from the 'Activity Accumulator table' recording all activity was used to generate the dataset for analysis. While the dataset can be used to obtain a range of different measures, for this paper we report on average click counts as a basic measure of activity in a course, for both students and teachers.

RESULTS

The data set was first cleaned by deleting data related to guest accounts and courses that were temporary or test sites. Next, courses related to non-standard subjects, such as "thesis," "practicum," "work integrated education" or "field work," were deleted. Finally, courses with no instructors, no students or both were deleted, along with courses with student enrolments of fewer than 11, as these were considered atypical of subject enrolments at the university. This left a total of 4520 Blackboard courses with usage logs for the 2014/15 academic year with at least one instructor and more than ten students enrolled in the course.

Overview of Blackboard Usage

For each of these 4520 courses, the average clicks per student in the course was calculated. A plot showing the percentage of all Blackboard courses at specific values for average clicks was produced (see Figure 1). As shown in Figure 1, 80 percent of all courses had an average number of clicks per student greater than or equal to 20, while around 20 percent of courses had an average number of clicks per student of between 0 and 20. At the higher end of the scale, less than 30 percent of courses had an average of 100 or more clicks per student.

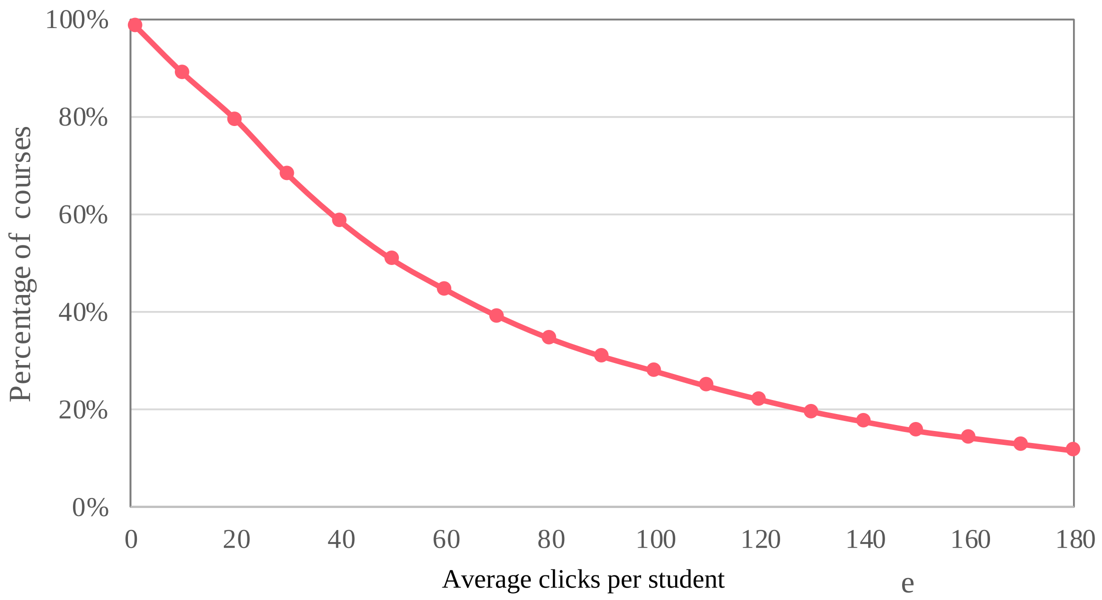

Figure 1: Percentage of Blackboard Courses with Average Number of Clicks per Student

Based on the distribution of average student clicks, four activity categories were created and each Blackboard course categorised according to the average number of clicks per student. These categories were: inactive (average number of clicks per student less than 1, *n*=62); low (1 ≤ average clicks ≤ 30, *n*=1377); medium (31 ≤ average clicks ≤ 100, *n*=1827) and high (average clicks >100, *n*=1254).

Activity Classification and Training in the LMS

From the university's training database, all teachers teaching courses that academic year who had undertaken training in the LMS (i.e., through the workshop program the university offered) from 2010/11 – 2013/14 were identified, and this information was mapped to the teachers in each Blackboard course for the academic year being analysed (2014/15). After mapping teachers who had participated in LMS training to the dataset, a total of 1578 courses with at least one teacher who had participated in at least one LMS training workshop were identified, with the remaining 2942 courses having no teachers in the course who had participated in LMS training offered by the university. The percentage of courses for each activity level with trained and untrained teachers is shown in Table 1. A chi-square analysis was conducted to determine if there is an association between whether or not a course has at least one teacher with LMS training and the level of student activity in the course. This analysis showed that the percentage of courses with different levels of student activity differed according to whether or not the course had at least one trained teacher, $\chi^2(3, N= 4520) = 121.39, p= .000$. While the proportion of courses classified as having a medium level of student activity did not differ in terms of the percentage with at least one trained teacher, there were more courses with teachers who attended at least one LMS training workshop classified as having a high level of student activity and fewer as low.

Table 1: Percentage of courses at each activity level with and without at least one trained teacher

Trained Teacher	Activity Level				
	Inactive	Low	Medium	High	Total
With none	1.7%	34.9%	40.2%	23.2%	100%
With at least 1	0.8%	22.2%	40.9%	36.1%	100%

To better understand how training and activity level in a course are related, the dataset was refined to only include courses with one instructor and no other teachers in the course. This reduced the number of courses to 2074, of which 563 (27.15%) had an instructor who had undertaken in-house LMS training and 1511 (72.85%) who had not. The rationale for selecting only those courses with one teacher was that this would ensure that the teacher had control over the course and the learning activities therein. Descriptive statistics for the two types of courses (trained teacher and no trained teacher) are shown in Table 2 for the average number of clicks by both students and teachers.

Table 2: Average clicks by students and teachers in courses with and without a trained teacher

Trained Teacher	Average Clicks Per Course	
	Student	Teacher
With non (n=1511)	56.17	118.06
With 1 trained teacher (n=563)	71.31	187.70

Regardless of whether or not the teacher had participated in training or not, the average number of clicks by students was significantly correlated with the average number of clicks by teachers (r=0.592, p=.000, N=2074). This suggests that the more active a teacher is in a course, the more active their students are. A comparison of average number of clicks for students and teachers between the two types of courses (trained teacher and no trained teacher) was made using two separate independent samples t-tests. The results showed that the average number of clicks by students in a course was significantly higher for courses where the teacher had participated in training compared to those courses where the teacher had not ($t(2072)=4.307, p=.000$). Similarly, where the course was taught by a teacher with training, the average number of clicks by the teacher was significantly greater than for courses taught by teachers who had not participated in training ($t(2072)=5.265, p=.000$). Table 3 shows the percentage distribution for each activity category broken down by training status (teacher attended training, teacher did not attend training). Chi-square analysis of courses with teachers who were either trained or not trained by activity level confirmed that more courses classified as having high student activity were taught by teachers who had participated in training ($\chi^2(3,N= 2074) = 23.48, p= .000$).

Table 3: Percentage of courses with only one instructor at each activity level by training status

Training Status	Activity Level				
	Inactive	Low	Medium	High	Total
Teacher has not attended training	3.1%	40.8%	39.7%	16.3%	100%
Teacher has attended at least one training workshop	2.3%	32.2%	40.9%	24.5%	100%

To investigate how teachers who have attended training use the LMS differently to those who have not, LMS usage for different tools was compare for courses with only one teacher. Courses classified as "inactive" were removed from the sample, which left a total of 2014 courses for analysis. Table 4 shows the comparison of students' average clicks across the three tools used most frequently in our Blackboard courses with and without a teacher who had attended training. As this table shows, a greater number of average clicks were recorded for these Blackboard features for trained teachers. In particular, students in courses taught by teachers who attended training run by the University appear to make greater use of communication tools such as announcements and discussion board, although use is still quite low. In addition, students clicked on more content on average if they were in a course taught by a teacher who had undergone training.

Table 4: Average of clicks by all students in a course for selected blackboard features for courses with and without a trained teacher

Blackboard Feature	Average Clicks By Students Per Course	
	Trained Teacher *n*=550	Untrained Teacher *n*=1456
Content	61.03	48.25
Announcement	2.07	1.84
Discussion Board	2.98	1.87

The effect of class size together with training status was investigated using a two-way analysis of variance (ANOVA) with the between subjects factors of class size (four levels based on number of students enrolled: 30 or less, 31- 60, 61-100 and over 100) and training status (teacher attended in-house training, teacher has not attended in-house training). The dependent variable was the average number of clicks per students, which was used as it already takes into account class size. Helmert and Difference contrasts were used to examine differences between means for the four levels of class size. Descriptive statistics for this analysis are shown in Table 5. The results of the two-way ANOVA showed significant main effects for class size $f(3, 2006)=7.152$, $p=.000$ and training $f(1, 2006)=6.124$, $p=.013$, but no interaction effect. Contrast tests showed that the average number of clicks per student was significantly less for classes of 30 or less students, and significantly higher for classes over 100. Furthermore, students in courses with a teacher who had undergone in-house training made significantly more clicks on average than did those in courses where the teacher had not attended training.

Table 5: average student clicks by class size and whether the course was taught by a teacher who attended in-house training or not

Class Size	Average Clicks By Students Per Course					
	Total		Trained Teacher		Untrained Teacher	
Enrolment	Mean	*n*	Mean	*N*	Mean	*n*
<31	50.89	832	65.44	180	46.88	652
31-60	70.49	658	75.77	213	67.97	445
61-100	64.07	368	77.83	109	58.27	259
Over 100	81.28	156	77.86	48	82.80	108
TOTAL	62.06	2014	72.98	550	57.98	1464

Given that clicks on content were the most frequently occurring activity, the effect of class size together with training status on average number of clicks on content was investigated using a two-way analysis of variance (ANOVA). The between subjects factors were class size and training status as defined in the previous analysis. The dependent variable was the average number of clicks on content per student, a variable which already takes into account class size. Helmert and Difference contrasts were used to examine differences between means for the four levels of class size. Descriptive statistics for this analysis are shown in Table 6. The results of the two-way ANOVA showed significant main effects for class size $f(3, 2006)=7.624$, $p=.000$ and training $f(1, 2006)=10.763$, $p=.001$, but no interaction effect. Contrast tests showed the same pattern of results as the analysis of overall average click counts - that is, the average number of clicks per student on content was significantly less for classes of 30 or less students and significantly higher for classes over 100. Furthermore, students in courses with a teacher who had undergone in-house training made significantly more clicks on content on average than did those in courses where the teacher had not attended training. The final analysis we conducted was a two-way ANOVA using the same factors as the previous analyses, but with the dependent variable being the proportion of overall average clicks attributed to clicking on content. This analysis showed no significant main or interaction effects. Overall, content clicks accounted for between 72 and 82 percent of students' clicks in a course regardless of class size or whether the teacher had undertaken in-house training or not.

Table 6: average student clicks on content by class size and whether the course was taught by a teacher who attended in-house training or not

Class Size	Average Clicks By Students Per Course					
	Total		Trained Teacher		Untrained Teacher	
Enrolment	Mean	*n*	Mean	*n*	Mean	*n*
<31	42.21	832	52.93	180	39.25	652
31-60	59.97	658	63.31	213	58.37	445
61-100	55.30	368	68.37	109	49.80	259
Over 100	59.48	156	64.64	48	57.19	108
TOTAL	51.74	2014	61.03	550	48.25	1464

DISCUSSION

Data from online courses taught in one academic year were compared for two groups of teachers – one where teachers had participated in LMS-related training run by the university and one where the teachers had not. The purpose of this was to understand what differences there are in relation to use of the LMS by both students and teachers between these two groups. When comparing activity levels between groups, more courses classified as high activity had at least one teacher who had attended training. For courses with only one teacher, average clicks in a course made by teachers and students was significantly higher if the teacher had attended training. The results also showed that regardless of whether teachers had previously attended LMS training or not, the more active a teacher was in a course, the more active their students were. That training is associated with higher levels of online activity suggests that participants have transferred what they learned into practice – after training, participants should have a better understanding of the technical aspects of using the LMS and how to use tools in their online teaching. The greater number of average clicks by teachers who attended training and their students is consistent with this. However, transfer of learning from training can explain the increased activity of teachers in the LMS. Why students are more active remains to be answered, but we can tell from the data that the additional level of student activity in LMS courses taught by trained teachers comes mainly from clicking on content.

That students in our LMS courses click more frequently on content when the teacher has attended training suggests that trained teachers make more use of content as a learning activity in their online courses than do teachers who have not. However, it is not possible to determine from the data whether the number of clicks is greater for students in courses taught by trained teachers because there is more content, students click on the same content several times or both. In future extractions of data from the LMS, we intend to investigate why content clicks are higher in courses taught by trained teachers to answer these and other questions. From our analysis, as class size increased, the number of content clicks by students increased, regardless of the training status of the teachers. This suggests that provision of online content is a strategy that teachers employ to manage increased class size. However, clicking on content does not necessarily result in high levels of cognitive engagement, particularly if the content is a page of text or even a video that students watch. What students have to do with the content is what creates the level of cognitive engagement, such that making notes from a website or a video raises the level of engagement, as does having students answer questions about the material or participating in a discussion forum on the topic.

Therefore, if training results in teachers using more content in their courses, an opportunity exists to help teachers understand how to use content in a way that encourages deeper levels of engagement, rather than just surface processing of information. Researchers such as Morris et al (2005) have shown that students who engage with the course learning activities with greater frequency are the ones who are successful in the course. Therefore, it is a good sign that our students are more active if the teacher has participated in training, even though the increased activity seems to be mainly around accessing content, with some small increases in the use of discussion boards. A key challenge of provision of training is to help teachers to use content so that it encourages active learning and to help them explore the use of other tools in their online courses. Our analysis showed that there were a small number of courses taught by teachers who had not attended training that were classified as having high levels of student activity. In terms of understanding training effectiveness and delivery, it would be useful to know why these teachers have not participated in training and whether their use of the LMS could be enhanced if they did. However, these questions and others like them will most likely only be answered by supplementing analysis of data logs with other measures, such as interview or survey data. Just as mapping training information to the usage data provided insights about the effect of training on LMS use, we expect that including measures such as student grades and student ratings of teachers and teaching will greatly enhance the quality and usefulness of the information that can be obtained from analyzing this data.

CONCLUSIONS

Analysis of LMS usage logs presented in this paper suggests that where staff receive in-house LMS training, both students and teachers are more active in online courses. Although the measures used for the analyses reported here was quite coarse, useful information was still obtained and the findings raised many questions that can be explored through further analysis of the dataset. So, while it is time consuming to extract and clean data from the usage logs and then to make sense of the data, once this is done the dataset can be used to answer many questions about the online behavior of teachers and students without having access individual course sites. Our analysis supports the usefulness of training for increasing use of the LMS while at the same time providing insight into how to improve training so that teachers' online teaching is enhanced.

REFERENCES

Jurado, R. G., Pettersson, T., Gomez, A. R., &Scheja, M. (2014, November). Classification of the features in learning management systems. *Proceedings 17th Scientific Convention on Engineering and Architecture* (pp. 1-11), Havana, Cuba.

Lam, P., Keing, C., McNaught, C., & Cheung, K. F. (2006). Monitoring eLearning environments through analyzing web logs of institution-wide eLearning platforms. In L. Markauskaite, P. Goodyear, & P. Reimann, *Proceedings of the 23rd annual ascilite conference: Who's learning? Whose technology?*(pp.429-439). Sydney, Australia: Sydney University Press.

Lam, P., Lo, J., Lee, J., &McNaught, C. (2012). Evaluations of online learning activities based on LMS logs. In R. Babo, & A. Azevedo (Eds.), *Higher educationinstitutions and learning management systems: Adoption and standardization* (pp. 75-93). Hershey, PA: IGI Global.

Macfadyen, L. P.,& Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers and Education, 54*, 588-599.

Macfadyen, L. P.,& Dawson, S. (2012). Numbers are not enough. Why e-Learning analytics failed to inform an institutional strategic plan. *Educational Technology & Society, 15*(3), 149-163.

Montenegro-Marin, C. E., Cueva-Lovelle, J. M., Sanjuan, O., &Nuñez-Valdex, E. R. (2011). Towards an ontology to describe the taxonomy of common modules in learning management systems. *International Journal of Artificial Intelligence and Interactive Multimedia, 1*(4), 48-54.

Morris, L. V., Finnegan, C., & Wu, S. (2005). Tracking student behavior, persistence, and achievement in online courses. *Internet and Higher Education, 8*, 221-231.

Phillips, R. (2006). Tools used in learning management systems: Analysis of WebCT usage logs. In L. Markauskaite, P. Goodyear, & P. Reimann(Eds.),,*Proceedings of the 23rd annual ascilite conference: Who's learning? Whose technology?*(pp.663-673). Sydney, Australia: Sydney University Press.

Picciano, A. G. (2014). Big data and learning analytics in blended learning environments: Benefits and concerns. *International Journal of Artificial Intelligence and Interactive Multimedia*, *2*(7), 35-43.

Reyes, J. (2015). The skinny on big data in education: Learning analytics simplified. *TechTrends*, *59*(2), 75-80.

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

Saks, A.M. & Burke, L.A. (2012). An investigation into the relationship between training evaluation and the transfer of training. *International Journal of Training and Development*, *16*(2), 118-127.

Smith, V. C., Lange, A., & Huston, D. R. (2012). Predictive Modeling to Forecast Student Outcomes and Drive Effective Interventions in Online Community College Courses. *Journal of Asynchronous Learning Networks*, *16*(3), 51-61.

Walsh, P. (2015). Evaluating the Data Analytic Features of Blackboard Learn 9.1. *Irish Journal of Academic Practice*, *4*(1), Article 5.

Weaver, D. (2006). The challenges facing staff development in promoting quality online teaching. *International Journal on E-Learning*, *5*(2), 275-286.

Whitmer, J., Fernandes, K., & Allen, W. R. (2012, August 12). Analytics in progress: Technology use, student characteristics, and student achievement. *Educause Review Online*, 1-10. Retrieved September 15, 2016, from http://er.educause.edu/articles/2012/8/analytics-in-progress-technology-use-student-characteristics-and-student-achievement.