ASEAN Journal of Education
Journal homepage: http://aje.research.dusit.ac.th/

Factors Explaining Active vs Inactive Users of eLearning in a Blended Learning Context among University Students in Thailand

Darrin Thomas*

Faculty of Arts and Humanities, Asia-Pacific International University, Saraburi, 18180 Thailand

Article info

Article history:
Received: 24 February 2020
Revised: 6 May 2020
Accepted: 29 June 2020

Keywords:
eLearning, Blended learning, Thailand

Abstract

The use of blended learning has continued to grow yet its impact in terms of how actively engaged students are is not as thoroughly investigated. Therefore, the purpose of this study was to identify active and inactive users of a learning management system within the context of a blended learning experience at a tertiary institution in Thailand. A sample of 288 participants (n = 288) was taken from the research site. Utilizing a cross-sectional survey design, academic performance, course satisfaction, gender, class level, major, and attendance were used to distinguish between active and inactive users. In terms of predicting active users, the linear discriminant analysis showed an accuracy of 72 %, as well as a sensitivity of 81 %, and a precision of 75 %. The effect size was moderate for academic performance and attendance when comparisons were made between inactive and active users of the learning management system. Active users had higher academic performance, lower tardies, and fewer absences than inactive users. This indicates that active students generally perform better not only in traditional instructional environments but also in a blended learning context.

Introduction

The use of eLearning continues to grow in education. Half of all K-12 schools are expected to offer online courses by 2020 (Strauss, 2013). At the tertiary level, 30% of students are studying online (Seaman, Allen, & Seaman, 2018). Within Southeast Asia, there has been a growth in e-learning activity with an emphasis on English acquisition and study skills (Wichadee, 2018). This focus will more than likely expand as ASEAN nations push for additional technological development among their member nations.

Even with the transition to eLearning taking place, many faculty members at tertiary institutions remain skeptical of online education and continue to be proponents of face-to-face traditional instruction (Jaschik & Lederman, 2014). In light of this, there has been a push for blended learning which allows for the combination of eLearning with traditional forms of instruction (Cenejac, 2017). However, as with most change, the transition has not been without issues.

The move towards blended learning has not been without challenges. In the context of the online aspect, there are issues with maintaining engagement and having students navigate the learning experience alone (Cheng

* Corresponding Author
email: dtsac18803@gmail.com

& Chau, 2014). In addition, course satisfaction has been found to play a critical role in the performance of students (Skrbinjek & Dermol, 2019). Therefore, determining factors that encourage students to be active online while still considering the classroom context can be useful for instructors and administrators as they make the transition to offering blended learning at their campuses. This is critical in the context of Southeast Asia as eLearning and blended learning in particular are at the nascent of their development.

Studies have examined the role of course satisfaction, academic performance, attendance and demographic variables, such as gender class level, and major, in the past in their relation to blended learning (Brook & Beauchamp, 2015). However, none of these studies assessed the activity level of the student as the dependent variable. In addition, this combination of variables has not been examined together in a single study. As such, the purpose of this paper is to determine if course satisfaction, gender, attendance, major and academic performance are associated with whether an individual is an active or inactive user of the online platform in a blended learning context.

Objectives

The following objectives will be explored in this study:

1. To determine the sample's average perception in terms of academic performance, and attendance of the participants of this study.
2. To examine the relationship of active/inactive eLearning users when considering academic performance, attendance course satisfaction, major, class level, and gender.
3. To explore the demographic profile of active and inactive users of the eLearning platform in a blended learning experience.

Literature review

Blended learning is defined as a combination of traditional face-to-face instruction along with the use of information technology tools utilized over the internet (Okhwa & Lm, 2012), Models involving blended learning can focus on the impact or use of blended learning and or focus on the implementation of blended learning in specific subjects matters such as math, science, or any specific domain of learning (Alammary, Sheard, & Carbone, 2014). Generally, there is a goal of interactivity when examining the eLearning aspect of blended learning with regular patterns of activity being more beneficial for the learning of students (Sophonhiranrak, Suwannatthachote, & Ngudgratoke, 2015). As student connect socially with each other and the teacher they often perform better academically as well.

Blended learning has been found to influence course satisfaction. Studies have found that students who take courses utilizing blended learning have a more positive view of the course and see blended learning as better than classroom only instruction (Lin, Tseng, & Chiang, 2016). In particular, the use of the flipped classroom, a style of instruction in which students examine course readings and topics outside of class and experience activities and interaction in the class, influences engagement and satisfaction with a course (Fisher, Perényi, & Birdthistle, 2018). Blended learning has also been found to improve attendance with differences found by gender (Wicks, Craft, Mason, Gritter, & Bolding, 2015).

There are also several studies that look at blended learning. For example, the design of the course and the avoidance of multitasking have been found to play a role in the engagement of the learners (Manwaring, Larsen, Graham, Henrie, & Halverson, 2017). In addition, learner engagement is enhanced when the teacher demonstrates presence in the online aspect of the learning, encourages interactions between students online, and make clear connections between the online and classroom content (Nortvig, Petersen, & Balle, 2018). Lastly, blended learning cannot be developed in a vacuum as at least one study has found that ensuring engagement requires the unique characteristics of the learners (Tay, 2016).

Blended learning has also been found to play a role in academic performance. In a study of older adult students, blended learning was also found to boost test scores (Deschacht & Goeman, 2015). However, all studies do not lead to the same conclusion about blended learning. Weaker students do better academically when they experience traditional teaching rather than blended learning because they often lack the self-regulation needed to perform well academically when given autonomy over their learning (Broadbent, 2017). Therefore, blended eLearning success, like many aspects of education, is context dependent.

Academic performance

One of the main reasons for the use of blended learning is the belief that it can help with improving student's academic performance (Brook & Beauchamp, 2015). Academic performance has been found to be associated with course satisfaction and blended learning (Alshehri, 2017). One study found that there is a negative correlation between course satisfaction and GPA (Alshehri, 2017). Other studies have found that blended learning influences academic performance through its influence on emotions as well as the development of skill acquisition and comprehension of ideas (Bazelais & Doleck, 2018).

Online learners in particular develop a distinct set of skills from their learning experience. Generally, online learners are more adaptive or flexible and less dependent in terms of the support they need from the teacher (Vanslambrouck, Zhu, Tondeur, & Lombaerts, 2015). In addition, successful online learners usually experience less anxiety and worry in terms of their performance (Broadbent & Fuller-Tyszkiewicz, 2018). This implies that online learning clearly allows for the development of self-regulated learning skills at least among a subset of students.

Successful students also are found regularly accessing materials online particularly in a flipped classroom blended learning experience (Montgomery, Mousavi, Carbonaro, Hayward, & Dunn, 2019). In other words, strong students establish an online presence that helps them to understand the materials that they needed to learn. Despite the appreciation many students have for online learning, many students still prefer some form of offline materials, however, this was found primarily among adult learners and may not apply to young college students who just entered university (Vanslambrouck, Zhu, Tondeur, & Lambarets, 2015).

Course satisfaction

Course satisfaction can be described as a learning experience in which the subject matter is relevant, the instructor demonstrates subject-matter competence, classroom management is acceptable, and the student workload is reasonable (Howell & Buck, 2012). In terms of online learning, additional characteristics associated with course satisfaction includes eLearning readiness as well as an adequate design of the online portion of the course (Nortvig, Petersen, & Balle, 2018). Lastly, courses also needed to meet the criteria of higher convenience for students in the context of eLearning, which entails availability such as employing asynchronous learning approaches in the online aspects of the course (Vanslambrouck, Zhu, Tondeur, & Lambarets, 2015).

Gamification and the use of the flipped classroom have been associated with eLearning and blended learning. Gamification has been found to be unsuccessful in terms of motivation, empowerment, and satisfaction for students (Hanus & Fox, 2015). However, the flipped classroom has been found to not only improve academic performance but also to be positively associated with course satisfaction when comparisons were made to lecture style traditional teaching (Peterson, 2016). This may be because the classroom time involves social interaction while addressing problems while the content or theory is assimilated at a personal pace outside of class.

When a course is purely online students often show higher satisfaction with face-to-face instruction when comparisons are made (Tratnik, Urh, & Jereb, 2019). This may be due in part to a lack of online presence by the instructor, a lack of interaction with peers, and/or the design of the course (Nortvig, Petersen, & Balle, 2018). The online presence of the instructor and interaction with him or her has often been found to be a factor in a students' satisfaction with an online learning experience (Wengrowicz et al., 2018). Lastly, whether face -to-face, eLearning, or blended learning, it is important to make sure that the assessment of the student is perceived as fair to them and that there is some form of practicality to the learning (Sutherland, Warwick, Anderson, & Learmonth, 2018).

Research methodology

1. Population and samples

The setting of this study was an international university located in Central Thailand. The population of the study was approximately 1000 students. Stratified sampling by gender was used for determining the sample. A total sample of 288 participants was taken from 19 different courses that utilized a blended learning approach as the instructional experience. Teachers whose classes incorporated blended learning into their teaching use the learning management system for discussion forums, attendance, assignment submission, assessment (quizzes, and communication through messaging).

Class sizes vary in size from 6 to 33 students in a course. In the sample, 67 % were female vs 33 % who were male. In terms of class, 33 % were Seniors, 28 % were Juniors, 38 % were Sophomores and 1 % were Freshmen. Since Freshman are new to the tertiary experience, blended learning is not as rigorously practiced in freshman level classes at the site of this study. For major, 15 % of the participants were business majors, 6 % education majors, 6 % science majors and 73 % of the participants were English majors.

2. Research Instrument

A cross-sectional survey design was utilized in this study. The data was extracted from the university's learning management system (Moodle by the researcher). The extraction of data included demographic information such as gender, class level, and major. In addition, the main variables of this study, course grade (academic performance), attendance (absences and tardies), course satisfaction and eLearning activity were extracted from the learning management system as well.

Attendance was calculated based on the number of absences and tardies a participant had from the face-to-face class times during a semester. Course satisfaction was taken from the mean response of the participants to a course evaluation given by the university. The course evaluation addressed content and delivery as well as interaction and assessment. Example items from the 22-item evaluation includes "students were motivated to learn in this course" and "learning activities and test reflected the objectives and content of the course." Due to the sensitive nature of this information only the composite means of all items were made available for analysis by the university. The composite mean for the participants were sorted and values above the median were coded as "satisfied" and values below the median were coded as "unsatisfied."

eLearning activity was calculated by determining the number of clicks a participant made when performing different functions within the course page of the learning management system. More clicks indicated higher activity vs fewer clicks. Since the data was in the form of count information, a log transformation was performed to normalize it. Participants whose activity was above the median were coded as "active-users" and those whose activity fell below the 60th percentile were classified as "inactive-users". Table 1 provides a summary of the variables used in this study along with their level of measurement.

3. Data analysis

The means, standard deviations and confidence intervals were calculated for the descriptive data. Linear discriminant analysis was used to classify the examples as active or inactive users. The metrics used to assess the model's strength were accuracy, precision, recall, specificity, sensitivity, kappa, negative predictive value, and area under the curve. Accuracy is measured of the exactness of the model. Precision, recall, specificity, sensitivity, and negative predictive value are all metrics for measuring how well the model does at determining true/false positives and negatives. Kappa is used to take into account random guessing when make predictions and area under the curve is a metric that incorporates the tradeoff between sensitivity and specificity.

K-fold cross-validation was used to determine the generalizability of the results. Lastly, group means for active and inactive users was also calculated along with the effect size to allow for comparisons.

4. Ethics

Permission was obtained to collect data prior to the study. The individual respondents' identities were kept anonymous. In addition, the electronic results were kept secure. The risk in this study was low as the data that was utilized consisted of database logs of student activity in the learning management system.

Results

Table 2 provides the descriptive statistics of this study for academic performance, tardies and absences. Academic performance had a moderate negative relationship with absences. There was no relationship between tardies and academic performance. The other relationships were weak in nature and primarily negative with the exception being the weak positive relationship between absences and tardies. The correlational results indicate the collinearity is not a concern.

Table 3 provides the coefficient of the linear

Table 1 Linear discriminant coefficients

Variable	Measurement	Categories/Range
Academic performance	Continuous	1-100
Absent	Continuous	0-10
Tardies	Continuous	0-18
Major	Categorical	Business, Education, English, Science
Class level	Categorical	Freshman, Sophomore, Junior, Senior
Gender	Categorical	Male, Female
Course satisfaction	Categorical	Unsatisfied, Satisfied

Table 2 Means, standard deviations and correlations with confidence intervals

Variable	M	SD	95%CI	1	2
1. Late	3.53	3.37	3.14-3.93		
2. Absent	2.34	2.28	2.07-2.60	.20**	
			[.08, .30]		
3. Academic Performance	71.92	8.10	70.98-72.86	-.09	-.46**
				[-.20, .03]	[-.55, -.36]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

discriminant model. The dependent categorical variable of eLearning activity was divided into two categories (active & inactive user). The results indicate that academic performance, tardies, and a participant being an education major were weaker discriminant in the current model, which means they were not strong predictors of whether someone was an active or inactive user. However, being an English or science major, and being a sophomore or senior were stronger discriminants in the model, which means that these variables were better predictors as to whether someone was an active or inactive user. Being male or a junior were moderately strong discriminants in the model.

Table 3 Linear discriminant coefficients

Variable	Coefficients
Academic performance	-0.02
Absent	0.14
Major: Education	0.08
Major: English	1.72
Major: Science	1.40
Class: Junior	0.57
Class: Senior	1.08
Class: Sophomore	1.89
Tardies	0.05
Gender: Male	0.67
Course evaluation: Unsatisfied	-1.08

Table 4 shows the classification metrics based on a 10-fold cross validation. The dataset was divided into 10 different folds. The metrics were calculated for each and then averaged. The results indicate a model accuracy of 72 %. The kappa metric, with a value of 0.41, is a measure that takes into account the model's accuracy when taking into account chance and indicates some weakness in the model given the value. Sensitivity is the accuracy of the model of determining individuals who are really active eLearning users, which in this model measures at 81%. Specificity is the accuracy of the model to identify those who are inactive eLearning users, which in this model shows an accuracy of 60 %. Precision is a measure of the proportions that are truly positive or active users of eLearning, in this model the value is 75 %. High precision is indication of how relevant the model is. The negative predictive value is the accuracy of predicting that a person is an inactive user, which is 68 % in this model. The area under the curve is a measure of the model's ability to discriminate between those who are active and inactive users of eLearning, which in this model is 0.80 which is considered good.

Table 4 Model metrics

Metric	Value
Accuracy	0.72
Kappa	0.41
Sensitivity	0.81
Specificity	0.60
Precision	0.75
Negative predictive value	0.68
Area under the curve	0.80

Table 5 shows the group means and effect size of the continuous variables in this study for active an inactive eLearning users. Active users had a higher mean grade compared to inactive users. Active users also had on average fewer absences and tardies than inactive users. The effect size for academic performance, absences, and tardies are all moderately weak yet not trivially.

Table 5 Group means and effect size

	Active users	Inactive users	Effect size
Academic performance	73.36	70.95	0.30
Absences	1.86	2.66	0.35
Tardies	2.82	4.01	0.36

Discussion and conclusions

The results of this study have lead to several significant findings. First, based on the model metrics, the current model provides fairly decent accuracy for predicting active vs inactive users of eLearning in a blended context. Prior studies have always focused on predicting academic performance, course satisfaction, or self-regulation (Fisher, Perényi, & Birdthistle, 2018). With this study there are now indications of the measurable differences between those who are classified as active vs those who are classified as inactive.

Second, by identifying active and inactive users, it was possible to determine what were the difference between the two of them, active users have better grades, fewer absences, and fewer tardies when compared to inactive users of eLearning. This is consistent with other studies on academic performance in both blended learning settings and traditional face-to-face settings (Broadbent & Fuller-Tyszkiewicz, 2018). Stronger students appear to be stronger across most metrics that are used to assess academic performance or even the level of activity they show when using eLearning tools. This again points to the role of self-regulation and autonomy at least indirectly. Weaker students, as defined by their lower activity level in eLearning in this study, seem to lack the ability to come to class on time, miss more classes in general, and show lower academic performance, and this may be due to challenges with self-regulation (Broadbent, 2017).

A third finding is that even though there was a clear difference in the effect size of academic performance, absences, and tardies, the coefficients in the model show that these effects were weak when viewed concurrently in one model. In the model, it was the categorical variables that showed as stronger predictors of a student's activity level. In particular, being a Sophomore was considered one of the stronger predictors for determining activity level. In addition, being dissatisfied with a course was a strong predictor of not being an active user of eLearning. Course satisfaction has been associated with motivation in a prior study (Hanus & Fox, 2015). If a student is dissatisfied with a course they also tend to show signs of being less activity in the eLearning aspect as well.

The results of this study need to be limited to a similar context. In addition, linear discriminant analysis is primarily employed when the independent variables are continuous. However, linear discriminant analysis is robust enough to allow for the inclusion of categorical variables with care.

This study examined the relationship between user activity in the eLearning aspect of a course and attendance, academic performance, major, gender, course satisfaction. The results indicate that the independent variables reasonable predict the eLearning activity of the participants of this study. Teachers should be aware of the academic performance and course satisfaction when trying to assess a students' engagement in the eLearning aspect of a blended learning course.

Suggestions

Based on the results of this study the following recommendations are made. One, teachers must be sure to use teaching approaches that encourage attendance in face-to-face instruction as well as strategies that encourage high online activity. Examples of strategies that improve attendance includes the flipped classroom (Wicks et al., 2015). To increase eLearning activity, designing courses in a way that encourages a lot of peer interaction through the use of forums and online group projects can enhance eLearning activity and improve course satisfaction (Sophonhiranrak, Suwannatthachote, & Ngudgratoke, 2015).

Two, teachers must make sure that they are actively supporting students in both contexts of learning, which are in the classroom and online. For the online aspect, the teacher must demonstrate an online presence (Montgomery et al., 2019). This involves participating in forums, giving feedback on online assignments, posting information, and generally communication in the online context (Joksimović, Gašević, Kovanović, Riecke, & Hatala, 2015). In the classroom, support can be shown through providing scaffolding, setting high expectations, and even showing emotional support for students (Havik & Westergård, 2019).

In terms of further study, examining the association between self-regulated learning and eLearning activity either in a blended context or fully online would be beneficial. This study did not look at this relation specifically but there are implications that there may be some link between these two constructs due in part to the negative relationship found in this study between academic performance and tardies.

References

Alammary, A., Sheard, J., & Carbone, A. (2014). Blended learning in higher education: Three different design approaches. *Australasian Journal of Educational Technology, 30*(4), 440-454.

Alshehri, A. F. (2017). Student satisfaction and commitment towards a blended learning finance course: A new evidence from using the investment model. *Research in International Business and Finance, 41,* 423–433.

Bazelais, P., & Doleck, T. (2018). Investigating the impact of blended learning on academic performance in a first semester college physics course. *Journal of Computers in Education, 5*(1), 67–94.

Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education, 33,* 24–32.

Broadbent, J., & Fuller-Tyszkiewicz, M. (2018). Profiles in self -regulated learning and their correlates for online and blended learning students. *Educational Technology Research and Development, 66*(6), 1435–1455.

Brook, I., & Beauchamp, G. (2015). A study of final year education studies undergraduate students' perceptions of blended learning within a higher education course. *Educational Futures,7*(1), 18-38.

Cenejac, J. (2017, March 4). *5 blended learning trends that define higher education.* Retrieved 2018, June 25, from https://eLearningindustry.com/5-blended-learning-trends-that-define-higher-education

Cheng, G., & Chau, J. (2014). Exploring the relationships between learning styles, online participation, learning achievement and course satisfaction: An empirical study of a blended learning course. *British Journal of Educational Technology, 47*(2), 257–278.

Deschacht, N., & Goeman, K. (2015). The effect of blended learning on course persistence and performance of adult learners: A difference-in-differences analysis. *Computers & Education, 87,* 83–89.

Fisher, R., Perényi, Á., & Birdthistle, N. (2018). The positive relationship between flipped and blended learning and student engagement, performance and satisfaction. *Active Learning in Higher Education,* 1-17.

Hanus, M. D., & Fox, J. (2015). Assessing the effects of gamification in the classroom: A longitudinal study on intrinsic motivation, social comparison, satisfaction, effort, and academic performance. *Computers & Education, 80,* 152-161.

Havik, T., & Westergård, E. (2019). Do teachers matter? Students' perceptions of classroom interactions and student engagement. *Scandinavian Journal of Educational Research, 64*(4), 488 -507.

Howell, G. F., & Buck, J. M. (2012). The adult student and course satisfaction: What matters most? *Innovative Higher Education, 37*(3), 215–226.

Jaschik, S., & Lederman, D. (2014). Faculty attitudes on technology. Retrieved 2018, June 25, from https://www.inside highered. com/system/files/media/IHE-Fac TechSurvey2014%20final.pdf

Joksimović, S., Gašević, D., Kovanović, V., Riecke, B. E., & Hatala, M. (2015). Social presence in online discussions as a process predictor of academic performance. *Journal of Computer Assisted Learning, 31*(6), 638–654.

Lin, Y.-W., Tseng, C.-L., & Chiang, P.-J. (2016). The effect of blended lear ning in mathematics course. *Eurasia Journal of Mathematics, Science and Technology Education, 13*(3), 741–770.

Manwaring, K. C., Larsen, R., Graham, C. R., Henrie, C. R., & Halverson, L. R. (2017). Investigating student engagement in blended learning settings using experience sampling and structural equation modeling. *The Internetand Higher Education, 35*, 21-33.

Montgomery, A. P., Mousavi, A., Carbonaro, M., Hayward, D. V., & Dunn, W. (2019). Using learning analytics to explore self-regulated learning in flipped blended learning music teacher education. *British Journal of Ed ucation al Technology, 50*(1), 114-127.

Nortvig, A.-M., Petersen, A. K., & Balle, S. H. (2018). A literature review of the factors influencing e - learning and blended learning in relation to learning outcome, student satisfaction and engagement. *Electronic Journal of E-Learning, 16*(1), 46–55.

Okhwa, L., & Lm, Y. (2012). The emergence of the cyber university and blended learning in Korea. In C. J. Bonk, & C. R. Graham (Eds.), *The handbook of blended learning: Global perspectives, local designs*. San Francisco: John Wiley & Sons.

Peterson, D. J. (2016). The flipped classroom improves student achievement and course satisfaction in a statistics course: A quasi-experimental study. *Teaching of Psychology, 43*(1), 10-15.

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). *Grade Increase: Tracking Distance Education in the United States* (p.49). Retrieved 2018, June 25, from http://online Learningsurvey.com/reports/gradeincrease.pdf

Skrbinjek, V., & Dermol, V. (2019). Predicting students' satisfaction using a decision tree. *Tertiary Education and Management, 25*(2), 101–113.

Sophonhiranrak, S., Suwannatthachote, P., & Ngudgratoke, S. (2015). Factors affecting creative problem solving in the blended learning environment: A review of the literature. *Procedia-Socialand Behavioral Sciences, 174,* 2130-2136.

Strauss, V. (2013). Why K -12 online learning isn't really revolutionizing teaching. Retrieved 2018, June 25, from https://www.washingtonpost.com/news/answer-sheet/wp/2013/06/03/why-k-12-online-learning-isnt-really -revolutionizing-teaching/?noredirect=on&utm_term=.a977d323d5be

Sutherland, D., Warwick, P., Anderson, J., & Learmonth, M. (2018). How do quality of teaching, assessment, and feedback drive undergraduate course satisfaction in U.K. Business Schools? A comparative analysis with nonbusiness school courses using the U.K. National Student Survey. *Journalof Management Education, 42* (5), 618-649.

Tay, H. Y. (2016). Investigating engagement in a blended learning course. *Cogent Education, 3*(1). 1135772.

Tratnik, A., Urh, M., & Jereb, E. (2019). Stu dent satisfaction with an online and a face-to-face Business English course in a higher education context. *Innovations in Education and Teaching International, 56*(1), 36-45.

Vanslambrouck, S., Zhu, C., Tondeur, J., & Lombaerts, K. (2015). *Motivational profiles of adult learners in online and blended learning.* Retrieved 2018, June 25, from https://search.proquest.com/openview/75b0c7bc 8ab3a8638e90220cfb6959a6/1?pq-origsite=gscholar &cbl=1796419

Wengrowicz, N., Swart, W., Paul, R., Macleod, K., Dori, D., & Dori, Y. J. (2018). Students ' collaborative learning attitudes and their satisfaction with online collaborative case-based courses. *American Journal of Distance Education, 32*(4), 283 – 300.

Wichadee, S. (2018). Significant predictors for effectiveness of blended learning In a language course. *The JALT CALL Journal, 14*(1), 25–42.

Wicks, D. A., Craft, B. B., Mason, G. N., Gritter, K., & Bolding, K. (2015). An investigation into the community of inquiry of blended classrooms by a faculty learning community. *The Internet and Higher Education, 25,* 53–62.