International Journal of Finance, Insurance and Risk Management
Volume XI, Issue 3, 2021

pp. 57-68

Controlling Attrition in Blended Courses by Identifying Students at Risk: A Case Study on MS-Teams

Submitted 10/08/21, 1st revision 24/08/21, 2nd revision 14/09/21, accepted 30/09/21

Vassilis Zakopoulos[1], Ioannis Georgakopoulos[2], Evaggelia Kossieri[3], Dimitrios Kallivokas[4]

Abstract:

Purpose: *The research objective is to address the problem of students' attrition by identifying students who are liable to fail their courses. Given that the blended courses have been on the boom, our research is directed into identifying students at risk in blended courses with a view to controlling attrition.*
Design/methodology/approach: *Students' behavioral engagement data were analyzed in terms of a binary logistics regression with a view to developing a model to decide on the risk factors. A binary variable was modeled to describe students at risk and students not at risk. The students' behavioral engagement data constituted the independent variables in our regression analysis whereas the variable describing students at risk was the dependent variable. The students' behavioral engagement data was collected by students' learning activities. The elearning part was implemented by MS-Teams. The data were collected after the final test. The regression analysis outcome was a classification table indicating the correct classification percentage of our model.*
Findings: *Factors related to the conventional part of the course-delivery process were not deemed to be significant. On the other hand, factors related to the elearning part, such as the number of the assessment quizzes completed and the total logins into MS-Teams appeared to play a cardinal role in the students' critical performance.*
Practical implications: *Our model could be verified by being applied to a plethora of blended courses with a view to generating a prediction model for students at risk for blended courses that share the same learning design.*
Originality/value: *The added value of our research is centered on the fact that our model could potentially be applied to any blended course in order to come up with the respective risk factors. The originality of our research lies in the fact that the issue of controlling students' attrition is not addressed in a fragmentary way. Thereby, a concrete methodology was developed on the basis of an established generic risk management framework.*

Keywords: *Blended courses, risk model, risk factors, students' attrition.*
JEL codes:
Paper Type: *A research study.*

[1]*Corresponding Author, Laboratory Teaching Staff, Department of Accounting and Finance, University of West Attica, Grecce, v.zakopoulos@uniwa.gr;*
[2]*Associate, Department of Accounting and Finance, University of West Attica, Greece, igtei@uniwa.gr;*
[3]*Lecturer, the same as in 2, kossieri@uniwa.gr;*
[4]*Lecturer, Department of Business Administration, University of West Attica, Greece, dkalliv@uniwa.gr;*

1. Introduction

The rapid evolution and the widespread of new technologies totally transformed education along with other aspects of everyday life in recent years. In Higher Education in a wide range of academic disciplines, new teaching methods and pedagogical approaches and models have been adopted and applied thanks to the innovative technological tools and applications that swiftly became available.

Therefore, blended or hybrid learning is gradually being prevailed over conventional teaching in order to deal with new challenges as those that emerge during crises. Blended or hybrid learning maintains a sufficient level of physical presence and simultaneously adds up the elearning technology to the course-delivery process. In that spirit, the online educational material is highly important in blended courses (Garrison and Arbaugh, 2007; Georgakopoulos *et al.*, 2020). In the face of corona virus pandemics, different asynchronous online learning platforms, such as Webex, Zoom and recently Microsoft (MS) Teams have become extremely popular in use in all various aspects of schooling and mostly at the academic level.

It is important to denote that many academic Institutions have used Moodle in the e-learning part of their blended courses. Nevertheless, during the pandemic, a lot of institutions have tested MS-Teams in the e-learning process. In comparison to Moodle, according to the study of (Krasna and Pesek, 2020) MS-Teams excels in the field of communication through innovative chat and video-conferencing capabilities. The MS-Teams superiority is sealed through the screen-sharing capability which enlivens the lectures and gives educators and students the opportunity to interact and exchange feedback. The study of (Davidson *et al.*, 2018) has focused on MS-Teams learning analytics, stressing on a non-centralized spreadsheet report which is available per assignment. In that spirit, online quizzes, questionnaires and other similar activities could be designed as assignments in order for educators to take advantage of the respective engagement analytics. For all the above reasons, MS-Teams could be deemed to be a potent tool to implement the e-learning part in a blended course.

However, a crucial problem emerges in any type of learning and that also holds for blended courses. This problem is called ‘attrition’ and it is another term to describe students’ dropout, laying emphasis on the students’ feeling of incompetence motivated by their liable failure in a specific course (Abu *et al.*, 2012; Beaubouef and Mason, 2005). In this paper we do not take into account social, economic or psychological factors which could favor attrition but our research is directed into relating attrition to the students’ failure to complete the requisite learning activities.

Thereby, the best way to control attrition is to identify students who are liable to be viewed as students at risk before the end of the course-delivery process. This paper demonstrates a risk model which identifies students at risk in blended courses after the first course-run. Hence, the risk model identifies students at risk in any subsequent course-run. On the ground that attrition is being activated by students' failure in learning activities, our model analyzes data related to students' involvement in learning activities.

2. Literature Review

One study has proved that the use of technology along with the interaction processes play a cardinal role in the students' performance in blended courses (Ismail *et al.*, 2018). Another study has indicated that students' final achievement in blended courses is affected by the technical system which reflects the role of the e-learning system in the course-delivery process (Wu and Hwang, 2010; Wu and Liu, 2013). The same argument is augmented by other studies (Owston *et al.*, 2013; Filippidi *et al.*, 2010; Keskin, 2019; Akbarov *et al.*, 2018; Maccoun, 2016; Vernardakis *et al.*, 2012; Alsalhi *et al.*, 2019; Saritepeci and Cakir, 2015).

An important research has analyzed students' engagement data in two blended courses in terms of a binary logistics regression and has proved that students' skills developed by learning activities is a strong predictor of students' performance (Volchok, 2018).

A plethora of studies have attempted to identify students at risk in elearning courses through a proper analysis of LMS engagement data (Macfayden and Dawson, 2010; Georgakopoulos *et al.*, 2018; Marks, 2000; Petropoulou *et al.*, 2007; Anagnostopoulos *et al.*, 2020; Zhang *et al.*, 2004; Appleton *et al.*, 2008; Zinn and Scheuer, 2006). However, these studies have not been tested in blended courses. On the other hand, another study has indicated that Moodle LMS engagement data could predict students' final outcome in blended courses (Georgakopoulos *et al.*, 2020).

Although most prediction models which are referred to in the global literature have been built on a Moodle Platform, there are some recent studies that focus on the MS-Teams potential in the e-learning process. These studies have proved that MS-Teams provides students with an interactive learning environment which stirs them into participating in the e-learning process. The studies have also pointed out that students' performance could be assessed through students' interaction with activities mounted on MS-Teams (Rojabi, 2020; Dias *et al.*, 2020).

3. Our Research Objective

Our research interest is centered on controlling attrition in blended courses by identifying the risk factors of students' liable failure. Our endeavor is directed into developing a risk model which will decide on students at risk after the first course-run. The risk model is based on a proper analysis of the data related to students' involvement in the learning activities. On the ground that elearning part appears to assume an important role in the course-delivery process in blended courses, our research also attempts to examine whether the students' behavioral engagement data related to the e-learning part have significant correlation to students' failure. In our study, the e-learning part is accomplished by well-orchestrated activities on MS-Teams.

4. Research Methodology

Our method includes the below stages (Vose, 2008; Georgakopoulos *et al.*, 2018):
1. Data Collection;
2. Risk Model Development;
3. Risk Model Verification.

4.1 Data Collection

The data collection process is centered on gathering all students' behavioral engagement data in regard to the conventional and e-learning part in the course delivery process. Regarding the e-learning part, a lot of statistically meaningful data are stored into MS-Teams repository such as:

- Students' Logins into a specific Presentation;
- Students' total logins into a Team;
- Resources viewed by Students;
- Students' grades on activities;
- Messages sent by Students through chat.

However, there is not so much meaningful data which are interrelated to the conventional part which could be easily measured except data related to students' attendance.

4.2 Risk Model Development

The collected data is being analyzed in terms of appropriate machine learning or statistical techniques with a view to building a model which will decide on the real risk factors. The real risk factors could be viewed as the ones which have significant contribution to the risk occurrence (Macfayden and Dawson, 2010; Georgakopoulos *et al.*, 2018; Anagnostopoulos *et al.*, 2020; Georgakopoulos *et al.*, 2020). In our case we employed a binary logistics regression analysis to answer to this purpose.

Being more elaborate, through the use of the previously cited techniques, students could be classified into appropriate groups. In our case, students were classified into students at risk and into students not at risk (Macfayden and Dawson, 2010; Georgakopoulos *et al.*, 2018; Anagnostopoulos *et al.*, 2020). In parallel, it is important to stress the fact that the classification is being implemented in the context of a specific numeric threshold which is called 'cut value'. In our case, the cut value was reflected by the number 5.

4.3 Risk Model Verification

Afterwards, the risk model is applied to a plethora of courses sharing the shame learning design. In the case that the risk model achieves a high classification percentage the risk model will lead to a prediction model. In any other case, the whole process is reviewed, and new data is collected in order to come up with another risk model. This paper focuses on the risk model development. The risk model verification is not presented in the context of this paper given that the risk model verification process is in the pipeline.

5. Applying the Research Methodology

The risk model development process is demonstrated for two courses delivered at the faculty of 'Accounting, Finance and Social Sciences' at the University of West Attica. It is essential to underline that the courses shared the same instructional design. These courses were 'Business Informatics' and 'Introduction to Statistics'. 200 students participated in the first course whereas 220 students participated in the second course. The students were not divided into groups with respect to their sex or other demographic characteristics. Students who didn't take the final test were not included in the sample of our study on the ground that they were viewed as outliers. Focusing on the courses' structure, it would be beneficial to explain that both courses were designed in the context of the below common activities:

1. Specific lectures delivered in class;
2. Planned lectures delivered through MS-Teams through appropriate meetings;
3. Theoretical Material in form of slides and pdf resources along with Self-assessment quizzes were mounted on MS-Teams;
4. Final Test (in a form of quiz), mounted on MS-Teams.

It is important to clarify that students should attend the specific lectures delivered in class, they should attend the planned lectures delivered through MS-Teams and they should participate in the final test. Additionally, students could use chat utility in the MS-Teams environment to send messages asking for extra help or expressing questions on the syllabus. It is essential to underline that students could use chat utility during lectures and therefore students' questions could be answered in real time. A Theoretical material, including slides and other pdf resources was mounted on MS-Teams to help students gain knowledge on the syllabus. In parallel, self-assessment quizzes enabled students to test themselves on the comprehension of the syllabus. It is important to denote that the specific lectures were delivered in class in order to help students make practice. Students were deemed to pass the course if they achieved a final score greater or equal to 5 on the final test.

We modeled the binomial variable student risk to describe students who were about to fail the course as it is suggested in the studies of (Macfayden and Dawson, 2010; Georgakopoulos *et al.*, 2018; Anagnostopoulos *et al.*, 2020; Georgakopoulos *et al.*, 2020). The state “0” was modeled to indicate students not at risk whereas the state “1” was modeled to indicate students at risk. We also modeled the below variables with respect to students’ interaction with the learning activities and the entire learning process.

- Number of resources viewed by students (ppt, pdf);
- Number of attended lectures by students (delivered through MS-Teams);
- Number of attended lectures by students (delivered in class);
- Number of self-assessment quizzes completed by students;
- Students’ total logins into MS-Teams (including logins into a Group and into a Presentation);
- Total number of messages sent by students;
- Final Test grade.

After the final exams, the below variables along with the student risk variable were employed in terms of a binary logistics regression analysis in order to come up with the risk model. It is also important to denote that the engagements’ data described by the respective variables were measured two weeks before the final exams given that students usually speed up the pace of their study a few weeks before the final exams.

6. Results

6.1 Binary Logistics Regression Analysis Outcome (Course 1)

The risk model for the first course (Table 1) accounts for 83.4 % (Nagelkerke R Square) of the risk factors denoting that only 16.6 % of the liable risk factors is not identified. Thereby, there are a small number of factors that could potentially lead to the students’ failure which is not identified through the use of our model. This argument is also enhanced by the fact that the Nagelkerke R square value was close to 1 (0.834), denoting a good ft to the results. Additionally, the Cox and Shell R Square value was 0.616, also close to 1, ensuring a good fit to the results (Allison, 2014; Menard, 2000; Smith and McKenna, 2013).

Another metric for a good model fitness is the Hosmer and Lemeshow Test. In our case, the Sig. Value of the Hosmer and Lemeshow Test was 0.358, greater than 0.05, indicating that the model fits well to the results (Hosmer *et al.*, 2000).

Table 1. *The Regression Model Fitness’ Metrics (Course 1).*

Metric	**Value**
Cox & Snell R Square	0.616
Nagelkerke R Square	0.834
Hosmer & Lemeshow Test (Sig. value)	0.358

Source: *Own study.*

The classification potential of our model is indicated into Table 2.

***Table 2**. Classification Percentage (Regression Model- Course 1)*

Overall Classification Percentage	89.7

***Source:** Own study.*

The model achieved an 89.7% correct classification percentage (Table 2) indicating that only 10.3% of the cases are not correctly classified, meaning that a small portion of students who were not at risk were classified into students at risk. Table 3 points out the real risk factors according to the Sig. Value.

***Table 3.** Coefficients (Regression Model-Course 1)*

Coefficients	**B (Coefficient Value)**	**Sign.**
Total Logins into MS-Teams	-0.027	0.04
Number of Assessment Quizzes completed	-1.961	0.000

***Source:** Own study.*

The real risk factors, having significant contribution to the reduction of the risk probability are the ones, the significance value of which is equal or less than 0.05. Thereby, according to the Sig. column on Table 3, these factors are the 'Total Logins into MS-Teams' and the 'Number of Assessment Quizzes completed'.

In detail, a unit increase in the "Total Logins into MS-Teams leads to a slight decrease (0.027 unit) in the probability of the risk occurrence, whereas a unit increase in the Number of Assessment Quizzes completed, leads to a 1.961. unit decreases in the respective probability.

6.2 Binary Logistics Regression Analysis Outcome (Course 2)

The model (Table 4) accounts for 71.5 % (Nagelkerke R Square) of the risk factors denoting that only 28.5% of the liable risk factors is not identified. It is also important to stress out the values of Nagelkerke R square and Cox and Shell R Square respectively (0.715; 0,528) which are close to 1, indicating a good fit to the results (Allison, 2014). In parallel, the 'Sig. value' of the Hosmer and Lemeshow Test is 0.310, greater than 0.05, augmenting the argument that the model fits well to the results (Hosmer *et al.*, 2000).

***Table 4.** The Regression Model Fitness' Metrics (Course 2)*

Metric	**Value**
Cox & Snell R Square	0.528
Nagelkerke R Square	0.715
Hosmer & Lemeshow Test (Sig. value)	0.310

***Source:** Own study.*

The classification potential of our model is indicated into Table 5.

Table 5. Classification Percentage (Regression Model- Course 2).

Overall Classification Percentage	88.0

Source: *Own study.*

The second model achieved an 88.0% correct classification percentage denoting that only 12 % of the cases were not correctly classified, meaning that a small portion of students who were not at risk were classified into students at risk.

Table 6 points out the real risk factors in terms of the second course according to the 'Sig. value'.

Table 6. *Coefficients (Regression Model-Course 2)*

Coefficients	**B (Coefficient Value)**	**Sign.**
Number of Assessment Quizzes Completed	-1.050	0.000

Source: *Own study.*

The real risk factors, which have significant contribution to the reduction of the risk probability, according to the Sig. column on Table 6 is the "Number of Assessment Quizzes completed".

In detail, a unit increase in the "Number of Assessment Quizzes completed", according to column B on Table 6 leads to a decrease (1.050 unit) in the probability of risk occurrence.

7. Discussion

Both models fit well to the results, proved by all fitness metrics (Tables 1 and 4) The first model accounts for the 83.4 % of risk factors whereas the second model accounts for the 71.5 % of the risk factors (Nagelkerke R Square Value on Tables 1 and 4). Thereby, a small number of risk factors are not identified. The same holds true in other studies (Macfayden and Dawson, 2010; Georgakopoulos *et al.,* 2018; Anagnostopoulos *et al.,* 2020; Georgakopoulos *et al.,* 2020). Both models achieve a high classification percentage (89.7; 88.0 correspondingly in Tables 2 and 5), insinuating that there is a small number of cases which are not well classified.

Shedding more light on the cases, we can deduce that factors related to a conventional way of course delivery (such as lectures attended in class) were not deemed to be significant risk factors of students' failure in both courses. On the other hand, factors which are affiliated with a modern way of course delivery (total logins into MS-Teams and self-assessment quizzes completed) appeared to be significant in the reduction of the probability of the risk occurrence.

However, these factors were not the same for both courses, a finding which is in accordance with other studies (Macfayden and Dawson, 2010; Georgakopoulos *et al.,* 2018; Anagnostopoulos *et al.,* 2020; Georgakopoulos *et al.,* 2020). It is also important to underline that the e-learning part appeared to play a significant role in the students' final achievement in the context of both courses. That finding is in line with another study (Filippidi *et al.*, 2010).

In parallel, (students' logins into MS-Teams and self-assessment quizzes completed) which constitute to be factors in regard to students' effort and study have proved to be significant factors which critically affect students' performance in these courses, proving that students' behavioral engagement is a cardinal factor which affects their final achievement in blended courses. Given that self-assessment quizzes completed reflects the extent to which students take in the rudimentary knowledge, our study has indicated that students' practice through well designed self-assessment exercises appears to assume a cardinal role in students' performance, a finding which is greatly important from an educational aspect.

On the other hand, students' practice in class has not appeared to be correlated to their performance. In parallel, the total number of attended lectures delivered in class and in the MS-Teams meetings has not appeared to affect their performance. In other words, passive participation (reflected by students' absences has not appeared to constitute risk factor, a finding which is not in line with the philosophy of conventional teaching as it is proved in some studies (Georgakopoulos and Tsakirtzis, 2021; Tsakirtzis and Georgakopoulos, 2020). This also strengthens the argument that the conventional part didn't appear to be significantly correlated to the students' critical final learning outcome in these blended courses. However, that doesn't hold true for any blended course on the ground that the risk factors derive from respective risk models which are course dependent.

Another important finding is encircled on the fact that the number of students' messages through chat has not been included in the risk factors, although according to a specific study (Macfayden and Dawson, 2010), messages sent by students have proved to be correlated to their performance.

8. Conclusion

This paper has demonstrated a way to develop a risk model to identify factors of students' performance in blended courses through a proper analysis of students' behavioral engagement. Our study has proved that students' interaction with well-orchestrated activities on MS-Teams could be a main factor which affects their performance. The study has also demonstrated that the e-learning part in blended courses could be implemented by MS-Teams.

The study has also pointed out that the e-learning part assumes a major role in blended courses. It is important to stress the fact that our team is currently working on generating a prediction model of students' performance based on risk factors in the context of the respective courses, aiming at further examining the role of MS-Teams learning analytics in predicting students' final achievement.

Additionally, the impending prediction model could vouch for the control of students' attrition on the ground that students' critical performance could be predicted. It is also important to highlight that our research could potentially be expanded to examine other intrinsic features of students' attrition in order to examine risk factors which are not related to students' performance.

References:

Abu, S., Adera, B., Kamsani, S.R., Ametepee, L.K., 2012. Addressing the Increasing College Student Attrition Rate by creating Effective Classroom Interaction. Review of Higher Education & Self-Learning, 5(16).

Akbarov, A., Gönen, K., Aydogan, H. 2018. Students' Attitudes toward Blended Learning in EFL Context. Acta Didactica Napocensia, 11(1), 61-68.

Allison, P.D. 2014. March. Measures of fit for logistic regression. In Proceedings of the SAS global forum 2014 Conference, 1-13.

Alsalhi, N.R., Eltahir, M.E., Al-Qatawneh, S.S. 2019. The effect of blended learning on the achievement of ninth grade students in science and their attitudes towards its use. Heliyon, 5(9), e02424.

Anagnostopoulos, T., Kytagias, C., Xanthopoulos, T., Georgakopoulos, I., Salmon, I., Psaromiligkos, Y. 2020. Intelligent predictive analytics for identifying students at risk of failure in moodle courses. In International Conference on Intelligent Tutoring Systems, 152-162. Springer, Cham.

Appleton, J.J., Christenson, S.L., Furlong, M.J. 2008. Student engagement with school: Critical conceptual and methodological issues of the construct. Psychology in the Schools, 45(5), 369-386.

Beaubouef, T., Mason, J. 2005. Why the high attrition rate for computer science students: some thoughts and observations. ACM SIGCSE Bulletin, 37(2), 103-106.

Davidson, P., Long, E., Molnar, A., Chui, T.M., Ting, C.Y. 2018. MS Teams and Google classroom: Preliminary qualitative comparisons & user feedback. In 5th Pre-University Sunway Academic Conference.

Dias, S.B., Hadjileontiadou, S.J., Diniz, J. and Hadjileontiadis, L.J. 2020. DeepLMS: a deep learning predictive model for supporting online learning in the Covid-19 era. Scientific reports, 10(1), 1-17.

Filippidi, A., Tselios, N. and Komis, V. 2010. Impact of Moodle usage practices on students' performance in the context of a blended learning environment. Proceedings of Social Applications for Life Long Learning, 2-7.

Garrison, D.R., Arbaugh, J.B. 2007. Researching the community of inquiry framework: Review, issues, and future directions. The Internet and higher education, 10(3), 157-172.

Georgakopoulos, I., Kytagias, C., Psaromiligkos, Y., Voudouri, A. 2018. Identifying risks factors of students' failure in e-learning systems: towards a warning system. International Journal of Decision Support Systems, 3(3-4), 190-206.

Georgakopoulos, I., Chalikias, M., Zakopoulos, V., Kossieri, E. 2020. Identifying Factors of Students' Failure in Blended Courses by Analyzing Students' Engagement Data. Education Sciences, 10(9), 242.

Georgakopoulos, I., Tsakirtzis, S. 2021. Generating a Model to Predict Secondary School Students at Risk in Mathematics. International Electronic Journal of Mathematics Education, 16(2), em0630.

Hosmer, D.W., Lemeshow, S., Cook, E.D. 2000. Applied logistic regression 2nd edition.

New York: John Wiley and Sons Inc.

Ismail, A.O., Mahmood, A.K., Abdelmaboud, A. 2018. Factors Influencing Academic Performance of Students in Blended and Traditional Domains. International Journal of Emerging Technologies in Learning, 13(2).

Keskin, S. 2019. Factors affecting students' preferences for online and blended learning: Motivational vs. Cognitive. European Journal of Open, Distance and E-Learning (EURODL), 22(2), 72-86.

Krašna, M., Pesek, I. 2020. Influence of Moodle and MS Teams on teaching-learning-studying (TLS) processes. In 2020 43rd International Convention on Information, Communication and Electronic Technology (MIPRO) 612-616. IEEE.

Maccoun, H. 2016. The effect of using blended learning on the achievement of students and information retention of fifth graders in the biology course. J. Fac. Educ, 22(95), 209-240.

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.

Marks, H.M. 2000. Student engagement in instructional activity: Patterns in the elementary, middle, and high school years. American educational research journal, 37(1), 153-184.

Menard, S. 2000. Coefficients of determination for multiple logistic regression analysis. The American Statistician, 54(1), 17-24.

Owston, R., York, D., Murtha, S. 2013. Student perceptions and achievement in a university blended learning strategic initiative. The internet and higher education, 18, 38-46.

Petropoulou, O., Lazakidou, G., Retalis, S., Vrasidas, C. 2007. Analysing interaction behaviour in network supported collaborative learning environments: a holistic approach. International journal of knowledge and learning, 3(4-5), 450-464.

Rojabi, A.R. 2020. Exploring EFL Students' Perception of Online Learning via Microsoft Teams: University Level in Indonesia. English Language Teaching Educational Journal, 3(2), 163-173.

Saritepeci, M., Cakir, H. 2015. The effect of blended learning environments on student motivation and student engagement: A study on social studies course. Egitim ve Bilim, 40(177).

Smith, T.J., McKenna, C.M. 2013. A comparison of logistic regression pseudo R2 indices. Multiple Linear Regression Viewpoints, 39(2), 17-26.

Tsakirtzis, S., Georgakopoulos, I. 2020. Developing a Risk Model to identify factors which critically affect Secondary School students' performance in Mathematics. Journal for the Mathematics Education and Teaching Practices, 1(2), 63-72.

Vernadakis, N., Giannousi, M., Derri, V., Michalopoulos, M., Kioumourtzoglou, E. 2012. The impact of blended and traditional instruction in students' performance. Procedia Technology, 1, 439-443.

Volchok, E. 2018. Toward a predictive model of community college student success in blended classes. Community College Journal of Research and Practice, 42(4), 274-288.

Vose, D. 2008. Risk analysis: a quantitative guide. John Wiley & Sons.

Wu, W., Hwang, L.Y. 2010. The effectiveness of e-learning for blended courses in colleges: A multi-level empirical study. International Journal of Electronic Business Management, 8(4), 312.

Wu, J., Liu, W. 2013. An empirical investigation of the critical factors affecting students' satisfaction in EFL blended learning. Journal of Language Teaching & Research, 4(1).

Zhang, G., Anderson, T.J., Ohland, M.W., Thorndyke, B.R. 2004. Identifying factors influencing engineering student graduation: A longitudinal and cross-institutional study. Journal of Engineering education, 93(4), 313-320.

Zinn, C., Scheuer, O. 2006. Getting to know your student in distance learning contexts. In European Conference on Technology Enhanced Learning, 437-451. Springer, Berlin, Heidelberg.