Applying Learning Analytics for the Early Prediction of Students' Academic Performance in Blended Learning

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ABSTRACT

Blended learning combines online digital resources with traditional classroom activities and enables students to attain higher learning performance through well-defined interactive strategies involving online and traditional learning activities. Learning analytics is a conceptual framework and as a part of our Precision education used to analyze and predict students' performance and provide timely interventions based on student learning profiles. This study applied learning analytics and educational big data approaches for the early prediction of students' final academic performance in a blended Calculus course. Real data with 21 variables were collected from the proposed course, consisting of video-viewing behaviors, out-of-class practice behaviors, homework and quiz scores, and after-school tutoring. This study applied principal component regression to predict students' final academic performance. The experimental results show that students' final academic performance could be predicted when only one-third of the semester had elapsed. In addition, we identified seven critical factors that affect students' academic performance, consisting of four online factors and three traditional factors. The results showed that the blended data set combining online and traditional critical factors had the highest predictive performance.

Keywords

Learning analytics, Educational big data, MOOCs, Blended learning, Principal component regression

Introduction

Blended learning, also known as hybrid learning or mixed-mode instruction, incorporates one or two learning strategies into traditional classroom teaching. In 1960, many computer programming courses relied on the Internet to deliver digital learning materials to students; for example, Programmed Logic for Automatic Teaching Operations, developed at the University of Illinois (Hart, 1995), provided teaching activities that could be conducted on a large scale to enable a single instructor to simultaneously teach a large number of students.

In recent years, blended learning has become a popular teaching strategy because of the development of data analysis and computation; for example, Ellis, Pardo, and Han (2016) integrated social networking into a one-semester course and monitored the behaviors of over 220 undergraduate engineering students. The researchers used the students' interactive records to examine how to help them succeed in a collaboratively driven course. Hong et al. (2016) adopted a web game to develop ten teaching scenarios. After 6 weeks of experimentation on 110 elementary school students, the researchers indicated that the students were highly motivated by the combination of game-based learning and traditional classroom activities. Huang, Yang, Chiang, and Su (2016) improved students' learning motivations and performance in an English course by incorporating a mobile-based vocabulary feedback application into a traditional classroom environment.

To gain benefits from blended learning, many educators have adopted the Online Assessment System (OAS) or Massive Open Online Courses (MOOCs) into their course design; for example, Awang and Zakaria (2013) integrated the OAS into an integral course for 101 college students. The results indicated that the OAS improved the students' learning performance. Lu, Huang, Huang, and Yang (2017) incorporated MOOCs into a course and the results showed evidence of a well-defined intervention strategy. The course not only facilitated the students' learning achievements but also increased their level of engagement. Although the aforementioned studies have explained the advantages of blended learning, many researchers have asserted that in blended courses, monitoring students' learning behaviors and habits is difficult because of the complex learning environment (Ellis et al., 2016; Hong et al., 2016; Huang et al., 2016). Furthermore, at-risk students cannot be identified, and thus timely interventions cannot be conducted to facilitate learning success (Tempelaar, Rienties, & Giesbers, 2015).

To help students achieve classroom success, educators in Europe and the United States have recently applied learning analytics. In 2011, *Horizon Report*, a report of educational trends, investigated the benefits and future trends of learning analytics (Johnson, Smith, Willis, Levine, & Haywood, 2011). The report defined learning analytics as an ideal framework to improve learning performance based on data of students' learning history. Because of the limitations of data analysis and computation, learning analytics has been considered as a conceptual framework since 2011. Because of the rise of big data technology, in 2016, a special issue of *Horizon Report* was released on learning analytics to highlight that the optimal time to incorporate learning analytics into classroom settings had arrived (Johnson et al., 2016).

In recent years, learning analytics has served as a conceptual framework for the analysis of course characteristics, and has included prediction of students' learning performance, educational data analysis process development (Hwang, Chu, & Yin, 2017), data collection, and timely intervention (Hwang, 2014). To develop a conceptual framework for learning analysis, many researchers have designed and implemented courses with strategies for learning analytics. Lu et al. (2017) measured student engagement in a virtual learning environment and intervened with the students' learning activities according to the engagement score. The results showed improvements in the students' final academic performance and their self-regulated abilities after applying learning analytics. Hachey, Wladis, and Conway (2014) collected the learning data of 962 students to determine the factors that influence their grade point averages (GPAs). The results showed that students with no experience of online learning obtained low retention rates and had low GPA scores. The researchers concluded that online learning and practice must be offered to students without relevant experience before the beginning of a course (Papamitsiou & Economides, 2014).

In our research, learning analytics is a conceptual framework and as a part of our Precision education used to analyze and predict students' performance and provide timely interventions based on student learning profiles. The idea of our Precision education is the same as of The Precision Medicine Initiative (see https://obamawhitehouse.archives.gov/node/333101), which was proposed by President Obama in his 2015 State of the Union address, the Initiative is a new research effort to revolutionize the medical treatment of disease. As addressed in this Initiative, most treatments were designed for the average patients as a result of one-size-fits-all-approach treatments which could be successful for some patients but not for others. With the same philosophy, we carry the idea of Precision medicine, which is to improve the diagnosis, prediction, treatment, and prevention of disease, and define the objective of our Precision education as the improvement of diagnosis, prediction, treatment, and prevention of learning outcome.

The previous studies have shown that the development of big data technology has enabled learning analytics to become a suitable method for facilitating student success. The advantage of blended learning is that huge quantities of learning data can be collected through learning management system (LMS) to enrich personal learning data. However, few case studies have been conducted on the effects of applying learning analytics in blended courses due to the complexity of learning environments and the diversity of data. To provide timely interventions for at-risk students through learning analytics in blended learning, the present study not only implemented a MOOC and OAS enabled Calculus course but also proposed a process for the early identification of at-risk students. To predict students' final academic performance, many studies have used only one data set: a subset of a blended course. To improve prediction performance, critical factors may need to be identified and prediction accuracy may need to be compared using a data set combining online and traditional learning activities. The following research questions were proposed:
RQ1. How early can we predict students' final academic performance?
RQ2. Which are the most critical factors that affect students' final academic performance in blended learning?
RQ3. Which type of data set (blended vs. online vs. traditional) is more effective for predicting students' final academic performance in blended learning?

Literature review

Identification of at-risk students

According to the learning analytics executive reports by Arroway, Morgan, O'Keefe, and Yanosky (2015) and Kuzilek, Hlosta, Herrmannova, Zdrahal, and Wolff (2015), the first stage of implementing learning analytics is to identify at-risk students. Moreover, at-risk student identification must be conducted as early as possible to allow sufficient time for instructors to conduct educational interventions to facilitate students' learning achievements. Early at-risk student identification originated from the implementation of an open course that yielded a high dropout rate (Yang, Huang, & Huang, 2017).

Many researchers have defined dropout as a risk of MOOCs and have designed prediction methods to identify the dropout group. Xing, Chen, Stein, and Marcinkowski (2016) collected data on 3,617 students' video watching behaviors in 2014 and developed a classification model to identify the students likely to drop out by the following week. The results suggested that the retention rate would have been higher if the instructors had conducted timely interventions based on the prediction results. Lara, Lizcano, Martínez, Pazos, and Riera (2014) collected historical data on 100 students in a virtual learning environment consisting of five variables and proposed a knowledge discovery system for dividing students into dropout and non-dropout groups. The researchers reached a 90% classification accuracy through a verification process involving 100 students. Thammasiri, Delen, Meesad, and Kasap (2014) compared several resample algorithms with 7 years of student interaction data to assess data imbalance. Moreover, the target data was 80% true, indicating that 80% of freshman continued their studies, and 20% as false, indicating that 20% dropped out. These results show that the combination of synthetic minority oversampling (SMOTE) and the support vector machine yielded a classification accuracy of 90%, which was an improvement on the 86% accuracy without resampling in 10-folder cross validation. In addition to online courses, numerous researchers have incorporated student learning performance prediction into traditional classroom settings. Hachey et al. (2014) used a unique combination of variables to construct several classification models and verified the models with historical data collected from a learning management system. The results indicated that if the goal is to predict the learning outcomes of students with online course experience, retention rate is a more useful variable than GPA. For all other goals, GPA is more favorable. The results of the aforementioned studies show that at-risk students can be identified through classification methods if at-risk is defined as potential course dropout. However, in contrast to some studies, which have used data from open courses and pure online courses, another group of researchers defined at-risk as students who failed or obtained low grades at the end of a course. Many researchers have since adopted this approach for predicting students' final academic performance.

Students' final academic performance prediction

To identify at-risk students based on their final grades, scores, or learning outcomes, educational data mining can be used to identify students' behavioral patterns and predict their grades (Romero & Ventura, 2010). Romero, López, Luna, and Ventura (2013) collected data on 114 students from an online discussion forum and separated them into several data subsets on a weekly basis before evaluating each data set's predictive accuracy through several data-mining methods. Romero et al. (2013) used the sequential minimal optimization classification algorithm and student interaction data before a midterm exam to achieve the highest accuracy for predicting student learning performance. Hu, Lo, and Shih (2014) developed an early warning system by using a decision tree classifier. The model was constructed from data on 300 students and contained 13 online variables, including for how long each student had used the system and how many documents had been read by each student in the preceding week. The results revealed a 95% accuracy in predicting whether students would pass or fail based on 1–4 weeks of data from a skewed data set. To verify which critical factors affect prediction performance, Villagrá -Arnedo, Gallego-Durán, Compañ, Llorens-Largo, and Molina-Carmona (2016) determined 8 variables for student behavior and 53 for learning activity from a learning management system. Villagrá-Arnedo et al. (2016) designed four experiments to validate a data set with different variable combinations. The results demonstrated that a data set with particular variables had the highest correlation coefficient with grades and could attain higher prediction accuracy than the others.

In addition to predicting student learning outcomes, one study used students' grades as prediction labels and marked students as at-risk if their prediction grades were below average. Meier, Xu, Atan, and van der Schaar (2016) used regression to design a neighbourhood selection process to predict students' grades. The researchers claimed that the proposed algorithm achieved 76% accuracy. Asif, Merceron, and Pathan (2014) used a naive Bayes classifier to demonstrate that students' grades in their final year of university could be predicted based on student data collected during freshman year. In addition, the researchers executed the feature selection process before classification and the results showed that the data set from which socioeconomic and demographic variables had been removed was reasonably accurate. Huang and Fang (2013) used students' final grades as prediction targets. To evaluate the prediction results, the researchers designed two quantitative indicators to transfer the regression mean square error into prediction accuracy. The final results showed that the students' final exam scores were predictable to 88% accuracy based on eight variables collected from a learning management system. Previous studies have explained that "at-risk" can generally be used to describe students who dropout, fail, or achieve low grades on courses. We can fulfil the critical requirement of learning analytics by using students' final grades or scores as prediction indicators and designing a data-mining methodology based on classification or regression for the early prediction of indicators.

Recent studies have used data collected from entire course periods, which is problematic because, through this method, students can only be determined as at-risk after the conclusion of a course, which is ineffective in real scenarios. Moreover, recent studies have used single data sets collected from virtual learning environments or classroom activities, which is ineffective for applying the results to blended courses that combine online and face-to-face learning. Therefore, we referred to recent studies to define the following four aspects for consideration: First, data must be divided into sub data sets based on duration (Hu et al., 2014; Romero et al., 2013). Second, critical factors must be identified to improve prediction accuracy (Asif et al., 2014; Villagrá-Arnedo et al., 2016); for example, Villagrá-Arnedo et al. (2016) reduced the number of variables from 61 to 23 without losing prediction accuracy. Third, a predesigned regression model used in previous studies called principle component regression (PCR) (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Çevik, 2015; Huang & Fang, 2013; Meier et al., 2016) was used. The model was also implemented and evaluated in our previous study. PCR involves performing principle component analysis (PCA) to calculate the principle components, some of which can be used as variables in multiple linear regression. Fourth, design indicators and acceptance criteria must be considered to evaluate prediction performance. Although the regression model provided several indicators to evaluate performance, it did not provide any accuracy indicator. Therefore, following the concept of prediction accuracy proposed by Huang and Fang (2013), we applied the cross-validation mechanism proposed by Golub, Heath, and Wahba (1979) to design indicators to evaluate prediction performance. Moreover, in recent studies, the acceptance of prediction accuracy ranged from 75% (Villagrá-Arnedo et al., 2016) to 95% (Hu et al., 2014).

Method and experiments

Participation and learning activities

The participants in this study were 33 male and 26 female students. The experiment was conducted in a Calculus course that ran from September 2015 to February 2016. This study utilized MOOCs and the OAS to improve freshman students' learning outcomes at a university in Northern Taiwan.

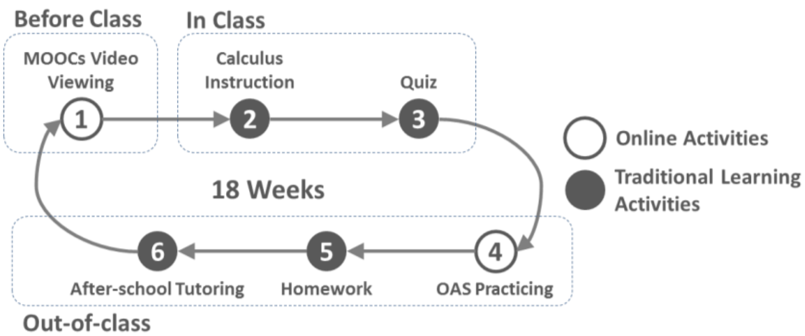


Figure 1. Calculus course learning activities

Table 1. Homework and quiz execution weeks

Weeks	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Homework		H1	H2	H3			H4	H5	H6				H7	H8	H9			
Quiz			Q1	Q2	Q3			Q4	Q5		Q6			Q7	Q8	Q9		

Table 2. Course content presented over 18 weeks (see http://mathweb.math.ncu.edu.tw/calc/maple-tutorial.html)

Week	Content	Week	Content	Week	Content
1	Function Limitation	7	Anti-differentiation	13	Vector Space
2	Differentiation	8	Number Integral	14	Curve in Space
3	Newton's Method	9	Harmonic series	15	Surface
4	Integral	10	Taylor Error	16	Scalar Field
5	Piecewise Function	11	Fourier Series	17	Multiple Integral
6	Arc Length	12	Polar	18	Line Integral

The Calculus course lasted for 18 weeks and included six learning activities (Figure 1). During the course, the participants used MOOCs to preview Calculus content through Open edX (see https://open.edx.org/about-open-edx) and practiced Calculus by using the OAS through Maple T.A. (see http://www.maplesoft.com/). To improve participants' mathematics ability, an instructor provided weekly after-school tutoring for each participant. To encourage the participants to continue studying Calculus, the instructor assigned paper homework exercises. To evaluate the students' learning performance for each topic, the instructor administered quizzes for specific weeks. The weekly quizzes, homework assignments, and course content are listed in Table 1 and Table 2.

Data sets of learning activities and variables

The MOOC and OAS enabled Calculus course collected participant learning profiles, which consisted of their video-viewing behaviors, out-of-class practice, homework assignments, and quiz scores. In particular, this study collected data on video-viewing behaviors from Open edX and data on out-of-class practice from the Maple T.A. Both types of data were categorized as online behavior. Table 3 lists the data variables definition for the Calculus course.

Table 3. Variables definition for the Calculus course

Variable	Description	Category	Learning environment
X_1	Number of days a student exhibits activity* per week	Online	MOOCs
X_2	Number of activities* a student engages in per week	Online	
X_3	Number of days a student watches videos per week	Online	
X_4	Number of videos a student watches per week**	Online	
X_5	Number of videos a student completely watches*** per week	Online	
X_6	Number of times a student clicks "Forward seek" or "Backward seek" during video viewing per week	Online	
X_7	Number of videos during which a student clicks "Pause" per week	Online	
X_8	Number of videos during which a student clicks "Stop" per week	Online	
X_9	Number of times a student clicks "Play" per week	Online	
X_{10}	Number of times a student clicks "Forward seek" per week	Online	
X_{11}	Number of times a student clicks "Backward seek" per week	Online	
X_{12}	Number of times a student clicks "Pause" per week	Online	
X_{13}	Number of times a student clicks "Stop" per week	Online	
X_{14}	Number of times a student engages in online practice per week	Online	OAS
X_{15}	Number of Calculus units a student practices per week	Online	
X_{16}	Number of days a student engages in online practice per week	Online	
X_{17}	Sum of days of practiced Calculus units per week	Online	
X_{18}	Student's weekly practice score	Online	
X_{19}	Student's weekly homework score	Traditional	Paper
X_{20}	Student's weekly quiz score		Paper
X_{21}	Number of times a student participates in after-school tutoring per week		Classroom
Y	Student's final academic performance		

Note. *MOOC activity refers to logging in to watch videos or browse course content. **Counting only once if repeated; unfinished video viewing is included. ***Completely" refers to more than 95%.

Process for predicting students' final academic performance

At-risk students can be identified as those with a predicted final academic performance of lower than 60. In the blended Calculus course, we applied a final academic performance prediction process with PCR consisting of data preprocessing, modeling, and evaluation phases. The data preprocessing phase consisted of data integration and data set separation. Data integration focused on integrating the learning data derived from MOOCs, the OAS, homework, quiz scores, and after-school tutoring. This study defined 21 variables from the blended learning environments consisting of data of online and traditional learning. The details of variables are described in Table 3. In the data set separation, the duration of the collected learning data was identified. The details of the proposed accumulated and duration data sets are described in the following section. In the modeling phase, a prediction model for students' final academic performance was generated through PCR. The evaluation phase was focused on measuring the goodness of fit and predictive effectiveness of the regression model. In the evaluation phase, this study measured not only the goodness of fit of the regression model by using the mean squared error (MSE), coefficient of determination (R^2), and Quantile–Quantile (Q–Q) plot but also the predictive performance of the regression model by using the predictive MSE (pMSE) and predictive mean absolute percentage correction (pMAPC), both of which were proposed in our previous study.

Experimental data set description

To investigate the influence of data set duration on predictive effectiveness, this study proposed accumulated and duration data sets. The purpose of the accumulated data set was to record learning data collected from the first week to a specified week, whereas that of the duration data set was to record the participants' learning behaviors during specific weeks. W_i^j indicates that the data set has collected data on the participants' learning behaviors from week i to week j. The accumulated and duration data sets included W_1^6, W_1^{12}, and W_1^{18} data sets and W_7^{12} and W_{13}^{18} data sets, respectively. W_1^6, W_1^{12}, and W_1^{18} were the three accumulated data sets that recorded students' learning behaviors from weeks 1-6, 1-12, and 1-18, respectively. W_7^{12} and W_{13}^{18} were the two duration data sets that recorded students' learning behaviors from weeks 7-12 and 13-18, respectively. The statistics for variables X_1-X_{21} based on the accumulated (W_1^6, W_1^{12}, and W_1^{18}) and duration (W_7^{12} and W_{13}^{18}) data sets are listed in Table 4 and **Error! Reference source not found.**.

Table 4. Statistics of variables for accumulated data sets (W_1^6, W_1^{12}, and W_1^{18})

Variable	Data set $\mathbf{W_1^6}$			Data set $\mathbf{W_1^{12}}$			Data set $\mathbf{W_1^{18}}$		
	Scale	Mean	*SD*	Scale	Mean	*SD*	Scale	Mean	*SD*
X_1	0.0-4.17	2.33	0.96	0.0-3.67	1.86	0.8	0.0-3.22	1.67	0.75
X_2	0.0-1410.33	482	254.34	0.0-839.0	321.6	176.13	0.0-594.39	257.13	142.16
X_3	0.0-3.0	1.26	0.66	0.0-2.0	1.04	0.54	0.0-2.11	0.94	0.51
X_4	0.0-10.33	4.26	2.67	0.0-10.42	3.74	2.42	0.0-8.61	3.3	2.15
X_5	0.0-10.0	2.7	2.3	0.0-9.42	2.33	1.94	0.0-7.5	2.1	1.69
X_6	0.0-7.33	2.42	1.86	0.0-6.83	2.11	1.63	0.0-6.22	1.9	1.42
X_7	0.0-7.83	3.07	2.05	0.0-7.08	2.69	1.75	0.0-6.5	2.45	1.61
X_8	0.0-9.67	2.37	2.21	0.0-8.92	2.05	1.86	0.0-7.11	1.78	1.55
X_9	0.0-309.33	48.96	55.58	0.0-255.33	43.42	47.65	0.0-220.5	40.68	42.1
X_{10}	0.0-154.83	13.99	23.36	0.0-85.08	10.83	16.2	0.0-57.61	8.85	11.94
X_{11}	0.0-28.5	4.92	5.71	0.0-21.17	4.26	4.77	0.0-21.33	4.34	4.5
X_{12}	0.0-43.5	11.47	10.34	0.0-30.67	9.38	7.67	0.0-32.78	9.57	7.71
X_{13}	0.0-11.5	2.61	2.5	0.0-10.25	2.25	2.08	0.0-8.22	1.95	1.73
X_{14}	0.0-8.5	4	2	0.0-7.08	3.03	1.54	0.0-7.17	2.53	1.54
X_{15}	0.0-2.17	1.55	0.62	0.0-1.83	1.15	0.48	0.0-1.61	0.89	0.41
X_{16}	0.0-2.33	1.09	0.51	0.0-1.67	0.83	0.4	0.0-1.22	0.64	0.33
X_{17}	0.0-3.17	1.8	0.79	0.0-2.25	1.34	0.63	0.0-1.94	1.03	0.52
X_{18}	0.0-9.12	5.99	2.33	0.0-8.91	5.55	2.07	0.0-8.89	5.41	1.97
X_{19}	0.0-9.99	9.09	1.61	0.0-9.99	9.12	1.55	0.0-9.98	9.06	1.63
X_{20}	0.0-9.94	7.83	1.85	0.0-9.94	7.67	1.9	0.0-9.89	7.33	2.02
X_{21}	0.0-4.0	0.14	0.6	0.0-4.0	0.14	0.6	0.0-4.0	0.14	0.6

In Table 4 and **Error! Reference source not found.**, "Scale" denotes the variable range from the minimum to maximum value. "Mean" and "*SD*" indicate the average and standard deviation values of 59 students, respectively. In the Calculus course, the average and standard deviation of the participants' scores were 70.05 and 19.2, respectively. The minimum and maximum Calculus scores were 25 and 100, respectively.

Table 5. Statistics of variables for duration data sets (W_7^{12} and W_{13}^{18})

Variable	Data set $\mathbf{W_7^{12}}$			Data set $\mathbf{W_{13}^{18}}$		
	Scale	Mean	*SD*	Scale	Mean	*SD*
X_1	0.0-3.33	1.38	0.85	0.0-3.0	1.3	0.9
X_2	0.0-537.33	161.21	151.9	0.0-436.17	128.19	113.98
X_3	0.0-2.5	0.82	0.65	0.0-2.5	0.73	0.61
X_4	0.0-10.5	3.21	2.97	0.0-6.83	2.44	2.03
X_5	0.0-8.83	1.95	2.2	0.0-5.5	1.63	1.55
X_6	0.0-7.83	1.79	1.83	0.0-5.0	1.49	1.33
X_7	0.0-7.67	2.32	2.11	0.0-6.0	1.97	1.68
X_8	0.0-8.17	1.74	2.08	0.0-4.83	1.23	1.23
X_9	0.0-247.33	37.87	50.74	0.0-261.0	35.2	43.91
X_{10}	0.0-68.83	7.68	13.8	0.0-26.5	4.87	6.51
X_{11}	0.0-30.33	3.6	5.46	0.0-21.67	4.51	5.13
X_{12}	0.0-32.67	7.28	7.98	0.0-49.83	9.96	10.45
X_{13}	0.0-9.0	1.89	2.26	0.0-5.17	1.34	1.36

X_{14}	0.0-5.67	2.06	1.51	0.0-12.5	1.55	2.22
X_{15}	0.0-1.5	0.75	0.46	0.0-1.17	0.39	0.38
X_{16}	0.0-1.67	0.56	0.4	0.0-0.83	0.27	0.27
X_{17}	0.0-2.33	0.88	0.62	0.0-1.33	0.42	0.43
X_{18}	0.0-8.7	5.12	2.05	0.0-8.85	5.14	1.91
X_{19}	0.0-9.99	9.15	1.52	0.0-9.97	8.94	1.88
X_{20}	0.0-9.94	7.52	2.06	0.0-9.89	6.65	2.48
X_{21}	0.0-4.0	0.14	0.6	0.0-4.0	0.14	0.6

Regression model estimation

The performance indicators for evaluating the prediction results in this study were the pMSE and pMAPC, both of which were proposed in our previous study. In the present study, we introduced 10-fold cross validation with shuffling to calculate the pMSE and pMAPC values. We used the testing data obtained from the 10-fold cross validation to calculate the prediction performance. The pMSE and pMAPC equations are as follows:

$$pMSE = \frac{1}{n_{test}} \sum_{i=1}^{n_{test}} (p_i - a_i)^2, \quad p_i \in p^{test} \ and \ a_i \in A \tag{1}$$

$$pMAPC = 1 - \frac{1}{n_{test}} \cdot \sum_{i=1}^{n_{test}} \left| \frac{p_i - a_i}{\bar{a}} \right|, \quad p_i \in p^{test} \ and \ a_i \in A \tag{2}$$

The symbols a_i and p_i represent the actual and predictive scores, respectively, of student s_i. $A = \{a_1, a_2, \ldots, a_n\}$ records each student's Calculus score. The symbol $\bar{a}$ represents the average score of all students in the blended Calculus course. $P^{test} = \{p_1, p_2, \ldots, p_{n_{test}}\}$ records the predictive Calculus score in the testing data. A lower pMSE value and higher pMAPC value indicate higher predictive performance and higher predictive accuracy, respectively. Therefore, our objective was to find a regression model with a lower pMSE and higher pMAPC.

Experimental results and discussion

Earliness of students' final academic performance prediction

Regression Model Estimation

We applied PCR to five data sets and generated 21 final academic performance prediction models for each data set. Table 5 lists the average values and scale of the R^2, adjusted R^2, and Durbin-Watson statistic for each data set. The Durbin-Watson values indicate that the 21 learning variables are independent. The ranges of the average R^2 and adjusted R^2 values for each data set are 0.34-0.47 and 0.30-0.38, respectively. These results are similar to those of previous studies (Agudo-Peregrina et al., 2014; Çevik, 2015), which indicates that the explanatory power of each regression model in the present study was acceptable. Regarding the scale of the R^2 and adjusted R^2, the scale ranges of the accumulated data sets are all higher than the scales of the duration data sets, which suggests that the explanatory power of the regression models using the accumulated data sets was higher than that of the regression models using the duration data sets.

Table 5. R^2, adjusted R^2, and Durbin-Watson values for five data sets

Dataset		R^2		Adjusted R^2		Durbin-Watson	
		Mean	Scale	Mean	Scale	Mean	Scale
Accumulated data set	W_1^6	0.47	0.16~0.66	0.37	0.15~0.52	1.70	1.4~1.99
	W_1^{12}	0.47	0.11~0.69	0.36	0.08~0.52	1.77	1.4~2.06
	W_1^{18}	0.48	0.10~0.72	0.38	0.08~0.56	1.87	1.47~2.18
Duration data set	W_7^{12}	0.34	0.01~0.70	0.31	0.02~0.53	1.69	1.49~1.88
	W_{13}^{18}	0.43	0.03~0.59	0.30	0.01~0.43	1.92	1.51~2.18

Regarding testing of the regression models, Table 6 lists the values of the F-test and corresponding significance level for each data set. Datasets W_1^6, W_1^{12}, W_1^{18}, W_7^{12}, and W_{13}^{18} had 21, 20, 20, 16, and 17 regression models, respectively. According to the conventional estimation results in Table 5 and Table 6, the accumulated data sets had regression models with better goodness of fit than those of the duration data sets.

Table 6. F-test values and corresponding significance levels for five data sets

Data set		Value of F-test		*p*-value of *F*-test		Number of significant	
		Mean	Scale	Mean	Scale	Not sig.	*Sig.*
Accumulated data set	W_1^6	4.93	3.29~11.24	0.001	1.92E-6~0.008	0	21
	W_1^{12}	4.50	2.32~7.25	0.006	3.32E-6~0.068	1	20
	W_1^{18}	4.75	2.21~6.53	0.007	7.63E-6~0.08	1	20
Duration data set	W_7^{12}	3.43	0.55~5.31	0.12	4.73E-5~0.65	5	16
	W_{13}^{18}	3.43	0.72~5.90	0.07	5.84E-5~0.54	4	17

Predictive performance of the five data sets

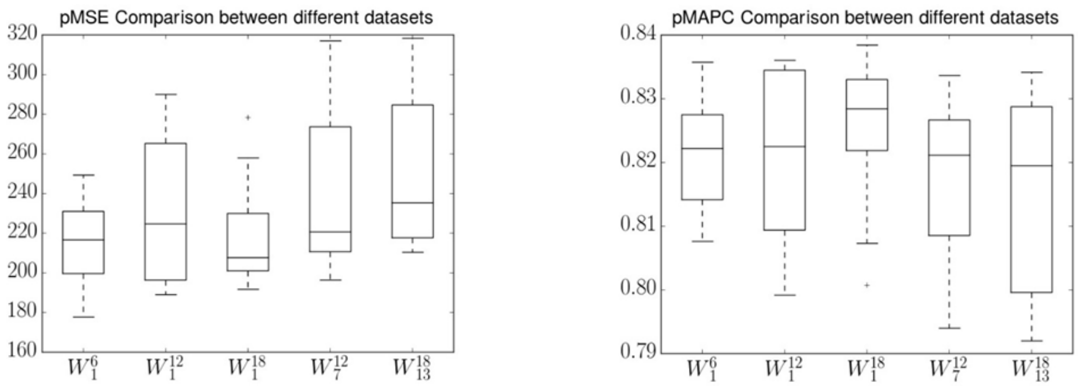
Table 7 lists the prediction indicators for the five data sets. The pMSE and pMAPC ranges among the data sets are 214-248 and 0.82-0.83, respectively. Regarding the mean of the pMSE, the accumulated data sets all had slightly lower means than did the duration data sets. However, according to the pMSE values, the predictive error for each participant's final academic performance in each of the five data sets was close to 15. By contrast, the mean range of the pMAPC among the accumulated and duration data sets was 0.82-0.83. Regarding the average pMSE and pMAPC values, predictive performance was fairly similar in the accumulated and duration data sets because some information may have been lost when computing the average. To solve this problem, this study conducted Wilcoxon signed-rank testing for the 21 regression models for each data set.

The results of Wilcoxon signed-rank testing of the five data sets are listed in Table 7. The Wilcoxon signed-rank test results for pMSE and pMAPC are listed in the lower and upper triangular matrices, respectively. For the Wilcoxon signed-rank tests for pMSE and pMAPC, the accumulated data sets W_1^6 and W_1^{18} had significantly different results to the duration data sets W_7^{12} and W_{13}^{18}, suggesting that the predictive performance was significantly different between the data set types. Furthermore, we applied box plots to determine which accumulated data set had the highest predictive performance.

Table 7. Results of predictive performance for the five data sets

		Mean of pMSE	Mean of pMAPC	pMSE \ pMAPC (Wilcoxon signed-rank test)				
				$\mathbf{W_1^6}$	$\mathbf{W_1^{12}}$	$\mathbf{W_1^{18}}$	$\mathbf{W_7^{12}}$	$\mathbf{W_{13}^{18}}$
Accumulate data set	W_1^6	214.85	0.82	-	0.00^{**}	0.61	0.01^{*}	0.00^{**}
	W_1^{12}	230.70	0.82	0.54	-	0.03^{*}	0.07	0.04^{*}
	W_1^{18}	217.06	0.83	0.05^{*}	0.00^{**}	-	0.00^{**}	0.00^{***}
Duration data set	W_7^{12}	239.62	0.82	0.01^{*}	0.07	0.00^{***}	-	0.07
	W_{13}^{18}	248.33	0.82	0.00^{**}	0.16	0.00^{**}	0.99	-

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.



(a) Results of pMSE comparison (b) Results of pMAPC comparison

Figure 2. Comparison of the pMSE and pMAPC results of different data sets

Figure 2 shows a box plot comparison of the different data sets based on the pMSE and pMAPC results. For each data set, we used box plots to describe the distribution of pMSE and pMAPC values for the 21 regression models obtained using PCR. The bottom and top lines represent the minimum and maximum values, respectively. From bottom to top, the three lines in the box indicate the lower quartile, median quartile, and upper quartile, respectively. Figure 2 shows that the box plots of the duration data sets are longer than those of the accumulated data sets, which indicates that the predictive performance of the accumulated data sets was more stable than that of the duration data sets. In addition, the minimum pMSE values of the accumulated data sets are lower than those in the duration data sets and the maximum pMAPC values of the accumulated data sets are higher than those of the duration data sets. The results of the pMSE and pMAPC comparison show that the accumulated data sets have better prediction ability than do the duration data sets.

The results of the pMAPC and pMSE comparison matrix show that among the accumulated data sets, W_1^{18} and W_1^6 had better predictive performance than did W_1^{12}. Compared with W_1^6, W_1^{18} had a higher maximum value and higher medial quartile for pMAPC, as well as a lower median quartile for pMSE. However, W_1^6 had the lowest pMSE value. These results show that W_1^{18} had a slightly higher predictive performance and accuracy than did W_1^6. Because of outliers in the maximum value of pMSE and minimal value of pMAPC, the stability of W_1^{18} was lower than that of W_1^6. In a real scenario, PCR would generate an equal number of regression results as variables of PCA. Thus, only one prediction result could be randomly selected from the results, which could cause issues if the data set had a wide range of prediction accuracy or in a data set with high average accuracy but few outliers such as W_1^{18}. Therefore, a convergent or stable data set is necessary even if its average accuracy is lower than that of other data sets. Thus, W_1^6 was determined to be the most suitable data set for real scenarios.

Linear regression residual analysis

According to the results of conventional regression and predictive performance estimation presented in the previous section, the accumulated data set W_1^6 had the highest stability and accuracy for predicting students' final academic performance. A final test was required to identify the characteristics of normalization, independence, and homogeneity in the data set. However, because PCA can project data into a vector space with a dimension with the same number of variables, 21 models were estimated for each data set. To follow up W_1^6, we had to select the most predictable components from the 21 PCR results.

Figure 3 shows the pMSE and pMAPC results for each principle component in data set W_1^6. The optimal pMSE and pMAPC values (178.94 and 83.5%, respectively) can be obtained in the 12 components. Figure 4 shows the results of linear regression residual analysis by using a Q–Q plot of 12 principle components of W_1^6. The distribution for all residuals closely resembles a straight line, which indicates that the distribution for the difference between the predicted and real values supports the characteristics of normalization, independence, and homogeneity.

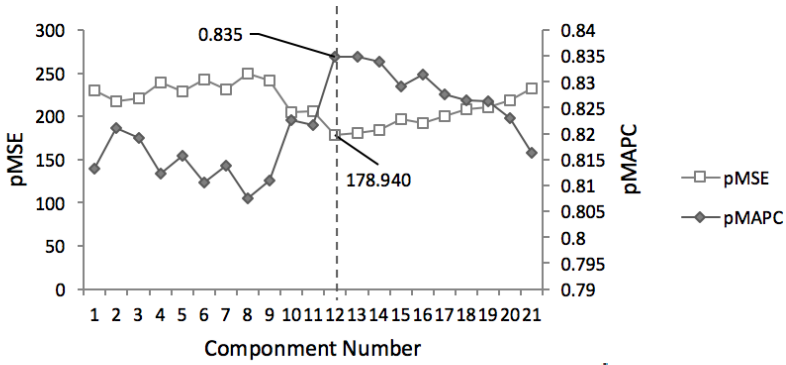


Figure 3. Results of pMSE and pMAPC for each W_1^6 component

To answer **RQ1** (How early can we predict students' final academic performance?), the results of the conventional and predictive performance estimations indicate that students' final academic performance can be predicted by the sixth week of the semester. The PCR model from data set W_1^6 had the highest stability and prediction accuracy, which is consistent with the findings of previous studies, which achieved early identification of at-risk students after one third of the course period had been completed (Hu et al., 2014) and before the midterm exam (Romero et al., 2013). Data set W_1^{18} had similar predictive accuracy and stability for predicting students' final academic performance because performance can be calculated using quiz or homework scores throughout the whole semester. Hu et al. (2014) asserted that to identify at-risk students within the learning analytics framework, offering intervention based on an 18-week prediction result is too late. Therefore, the present study recommends using accumulated data set W_1^6 to predict students' final academic performance. In addition, we found that the predictive performance of duration data sets is inferior to that of accumulated data sets, which indicates that the completeness of data collection is crucial for data analysis.

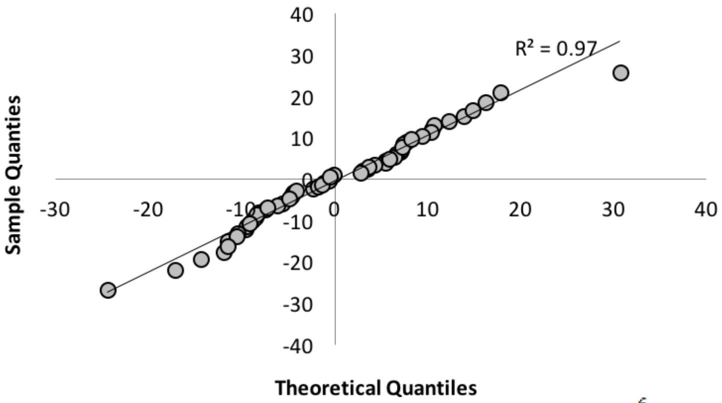


Figure 4. Q–Q plot of 12 components of data set W_1^6

Determining critical factors that affect students' final academic performance in blended learning

According to the summary of the literature review, the first step to predicting students' final academic performance is to determine as many variables as possible. Subsequently, rules should be applied to enable the selection of variables to obtain higher prediction ability. Moreover, according to the summary in previous section, data set W_1^6 had the highest stability and predictive accuracy, and thus we used this data set to determine the critical factors that affect students' learning performance. Table 8 shows the regression model estimation results. Components 1, 2, 5, 7, 9, 10, and 12 had a significant influence on students' final academic performance. For each significant component, we selected variables with higher coefficients as critical factors; for example, variable X_2 was selected as the critical factor for Component 1 because of the substantial differences between the coefficient of variable X_2 and those of the other variables.

Table 8. Variable estimation results of PCR for 12 components obtained using data set W_1^6

Variables	Components											
	1	2	3	4	5	6	7	8	9	10	11	12
X_1	0	-0.01	0.01	0	0	-0.01	-0.06	0.04	0.18	-0.14	0.21	0.01
X_2	**0.99**	-0.17	0.01	0.03	0	0	0.01	0	0	0	0	0
X_3	0	0	0.01	-0.01	0.02	0.03	-0.02	-0.06	0.16	-0.03	0.05	0.04
X_4	0.01	0	0.03	-0.13	0.2	0.34	-0.2	-0.08	0.5	0.12	0.03	0.14
X_5	0.01	0	0.05	-0.12	0.23	0.35	-0.13	0.08	-0.19	-0.04	0.09	0.08
X_6	0.01	0	-0.02	-0.08	0.15	0	-0.14	-0.15	0.37	0.28	-0.12	-0.36
X_7	0.01	0	0.03	-0.14	0.05	0.14	-0.1	-0.05	0.38	0.03	-0.05	0.33
X_8	0	-0.01	0.05	-0.12	0.24	0.36	-0.14	0.09	-0.26	-0.04	0.04	-0.02
X_9	0.16	**0.95**	0.26	0.06	-0.01	-0.01	-0.03	0.02	0	0.01	0	0
X_{10}	0.06	0.26	-0.94	-0.17	-0.06	0.12	0.03	0	-0.01	-0.03	0.01	0
X_{11}	0.02	0.03	-0.08	-0.24	**0.63**	-0.65	-0.29	-0.04	-0.09	-0.04	0.09	0.07
X_{12}	0.03	0.01	0.19	-0.9	-0.29	-0.06	0.22	-0.05	-0.04	-0.05	0.01	-0.05
X_{13}	0.01	-0.01	0.06	-0.12	0.3	0.39	-0.17	0.15	-0.29	-0.06	-0.06	-0.22
X_{14}	0	-0.02	0	-0.02	-0.21	-0.09	-0.31	0.67	0.24	-0.42	0.25	0
X_{15}	0	0	0	-0.01	-0.07	-0.03	-0.13	0.12	0	0.06	-0.06	0.05
X_{16}	0	0	0	0	-0.05	-0.01	-0.07	0.08	-0.02	0.02	-0.08	-0.02
X_{17}	0	-0.01	0	-0.02	-0.1	-0.03	-0.14	0.15	0.02	0.04	-0.11	0
X_{18}	0	-0.02	-0.02	-0.07	-0.31	-0.09	**-0.49**	0.2	-0.21	**0.62**	-0.22	0.08
X_{19}	0	0	0.01	0	-0.17	0	**-0.41**	-0.36	-0.03	**-0.55**	-0.59	0
X_{20}	0	-0.01	0.01	0.03	-0.27	0.04	**-0.43**	-0.5	-0.13	-0.01	0.65	-0.11
X_{21}	0	0	0	0	0	0.03	0.01	-0.09	-0.1	0.01	0.04	**0.81**
p value	$\mathbf{0}^{***}$	$\mathbf{0.009}^{**}$	0.881	0.637	$\mathbf{0.02}^{*}$	0.81	$\mathbf{0.006}^{**}$	0.114	$\mathbf{0.033}^{*}$	$\mathbf{0.001}^{**}$	0.099	$\mathbf{0.003}^{**}$

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

To address **RQ2** (Which are the most critical factors that affect students' final academic performance in blended learning?), this study determined seven critical factors that affect students' final academic performance, namely

X_2 (Number of activities a student engages in per week), X_9 (Number of times a student clicks "Play" during video viewing per week), X_{11} (Number of times a student clicks "Backward seek" during video viewing per week), X_{18} (Student's weekly practice score), X_{19} (Student's weekly homework score), X_{20} (Student's weekly quiz score), and X_{21} (Number of times a student participates in after-school tutoring per week).

X_{18}, X_{19}, and X_{20} are critical factors that affect students' final academic performance because of the evident relationships between each of these three variables and learning performance. The results are consistent with the findings of Huang and Fang (2013), who determined that exam scores and homework scores can predict students' final academic performance. Xing et al. (2016) asserted that online learning behaviors can predict dropout only in online courses. Based on our identification of four online variables, X_2, X_9, X_{11} and X_{18}, as critical factors that affect students' final academic performance, dropout and students' final academic performance may be related.

Ability of different data sets (blended vs. online vs. traditional) to predict students' final academic performance in blended learning

As mentioned in previous section, we identified seven critical factors that affect students' final academic performance in MOOC and OAS enabled blended courses. These seven critical factors can be categorized in W_1^6 as blended, online, and traditional data sets. Table 9 lists the categories of each factor and the PCR results. $W_1^6(O)$, $W_1^6(T)$, and $W_1^6(B)$ represent online, traditional, and blended data sets, respectively.

The results of R^2, the F-test, and the Durbin–Watson test, demonstrate that each indicator was acceptable for each data set (Table 9). The independent variables in three data sets are listed in Table 9. The regression tests for $W_1^6(O)$, $W_1^6(T)$, and $W_1^6(B)$ contained three, three, and five significant variables, respectively, which indicates that the selected critical factors are crucial for predicting students' final academic performance. In addition, the numbers of best components for the online, traditional, and blended data sets were all equal to the numbers of independent variables for each data set, which shows that each data set required whole independent variables to determine the optimal predictive performance. The blended data set $W_1^6(B)$ obtained the optimal pMSE and pMAPC values of 159.17 and 0.82, respectively. Figure 3 illustrates that the optimal pMSE in W_1^6 was 178.94, which was inferior to that of blended dataset $W_1^6(B)$. These results show that the selected critical factors not only reduce the number of variables for PCR but also improve prediction performance.

Table 9. PCR results of blended, online, and traditional learning data sets

Data set	Variables (critical factors)	*p* value	pMSE	pMAPC	Best Comp	R^2	*F*	Durbin-Watson
Data set which blended online and traditional critical factors $W_1^6(B)$	X_2	0.00^{***}	159.17	0.82	7 (DF = 7)	0.56	0.00^{***}	1.62
	X_9	0.01^{**}						
	X_{11}	0.15						
	X_{18}	0.00^{***}						
	X_{19}	0.1						
	X_{20}	0.11^{**}						
	X_{21}	0.01^{*}						
Data set of online critical factors $W_1^6(O)$	X_2	0.00^{***}	181.16	0.82	4 (DF = 4)	0.39	0.00^{***}	1.42
	X_9	0.03^{*}						
	X_{11}	0.40						
	X_{18}	0.00^{***}						
Data set of traditional critical factors $W_1^6(T)$	X_{19}	0.00^{**}	186.99	0.80	3 (DF = 3)	0.40	0.00^{***}	1.70
	X_{20}	0.00^{***}						
	X_{21}	0.03^{*}						

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

To answer **RQ3** (Which type of data set (blended vs. online vs. traditional) is more effective for predicting students' final academic performance in blended learning?), the blended data set obtained the most favorable predictive performance, demonstrating that the blended data set had a higher predictive performance than did the traditional data set. This result is consistent with the findings of Agudo-Peregrina et al. (2014), who revealed that students' interactions with online learning environments influence their academic performance. In addition, the present study followed previous studies in using critical factors to improve predictive performance (Asif et al., 2014; Romero et al., 2013; Villagrá-Arnedo et al., 2016).

Conclusion

This study collected student profiles from a MOOC and OAS enabled blended Calculus course. In addition, we applied PCR to evaluate five data sets that were separated based on the collected data. The experimental results demonstrate that students' final academic performance in a blended Calculus course can be predicted with high stability and accuracy by a data set containing data from weeks 1-6 of the course. In other words, through well-identified online and traditional variables, we were able to predict students' final academic performance when as early as one-third of the way through the semester. Seven critical factors that influence students' learning performance were identified by the regression model to improve prediction performance. However, explaining the relationship between these critical factors and learning performance would require investigation through interviews with educational experts. Furthermore, to achieve the goal of improving students' learning performance, the student performance prediction model proposed in this study and a well-defined intervention strategy must be integrated into the learning analytics framework. The complete learning analytics framework could be applied to predict student learning outcomes in the second semester of such a Calculus course.

Acknowledgments

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