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To Assess Blended Courses: Factors Influencing the Course Successful Rate

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The purpose of this study was to develop a model that can be used to assess blended courses at any given time during the semester, with concurrent data at the time, so adjustment to deal with possible problems could be made. Specifically, the model was developed to predict the successful rate of a blended course, with influential variables that reflect the efforts or activities of both students and the instructors. The sample of this study was 2238 blended courses offered from 24 colleges at a university in an eastern province of China. Data were collected at the end of spring semester of 2018 from the learning management system of the university. 24 predictor variables were examined, in which 14 were instructor related variables, 6 were student related variables, and 6 were general course activity. Multiple regression analysis was conducted. Three models were developed based on data from all courses, from liberal art colleges, and from STEM colleges. Overall, four direct influential variables and 13 indirect influential variables (including three student-related variables and 10 teacher-related variables) were found significant to the successful rate of a blended course. The findings clearly indicated that the efforts by students and instructors were both critical to the success of a blended course, and especially the instructors' work matters.

Keywords: blended course, assessment, influential factors, logistics

INTRODUCTION

Over the past two decades, blended learning has gradually become a commonly adopted approach in education from K-12 to higher education (Vo et al., 2024; Han & Ellis, 2019; Pulham & Graham, 2018). The term blended indicates a combined learning environment and a variety of methods or models of teaching and learning. An often-proposed definition of blended learning from the literature is that it is a combination of

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traditional place-based classroom methods and technology-mediated or online instruction, with elements of student control over time, place, path, or pace (Ausburn, 2004; Beaver, Hallar, & Westmaas, 2014; Han & Ellis, 2019; McGee & Reis, 2012; Bhagat et al., 2025). For this study, the focus was on blended courses with online instruction and face-to-face instruction at higher education level.

CURRENT TRENDS AND GAP IN RESEARCH

Currently, research on blended learning has shown several trends. The first trend was the comparison of learning outcomes between blended learning with traditional technology-free courses, some studies found no difference (Cosgrove & Olitsky, 2015), while some found that the blended learning environment provided more opportunities to perform collaborative learning and engage interactions (Cundell & Sheepy, 2018; Ma, et al.2015; Stap et al., 2024). The second trend was to explore the best practice in individual blended course design and examine the elements such as time, place, and pace with different models, such as rotation models or flex models (Beaver, Hallar, & Westmaas, 2014; Margulieux, McCracken, & Catrambone, 2016; Owston & York, 2018;Li & Wong, 2025; & Tomlinson, & Whittaker, 2013). Another trend was the use of technology tools in blended learning. For example, the use and design of instructional video or video modeling on students learning in blended courses (Borup, West, & Thomas, 2015; Wang, & Antonenko, 2017; & van Wermeskerken, Ravensbergen, & van Gog, 2018), along with the integration of gamified photography (Dini & Liu, 2017), and social media supported learning (Jelena et al., 2024).

Studies to examine factors that influence student learning in blended courses brought the research in this area to a higher stage with more advanced data analytics skills, and a variety of prediction models were developed and very nicely presented (Blieck, et al., 2019; Han, Wang, & Jiang, 2019; Mohammed & Alismaiel, 2019; Rennar-Potacco, Orellana, & Salazar, 2017; Li & Lin, 2024). On one hand, such studies provided useful guidance to educators who were to design or teach blended courses. On the other hand, a gap in research has also been revealed: after the models are developed, no follow-up studies are conducted to test them, or use them to actually perform assessments on blended learning. Furthermore, most of those studies were based on individual learners' performance and learning outcomes, so the models could only be used to predict individual learning.

STATEMENT OF THE PROBLEM AND PURPOSE OF THE STUDY

The core issue lies in assessment. Within our higher education system, the regular assessment, course evaluation for online or blended courses was conducted at the end of the course or semester (Baldwin & Yu-Hui, 2019). However, to that point, the improvement suggestions derived from these evaluations, which were formulated after the course concluded, could only enhance future classes. This study has two primary objectives, The first was to develop an initial prediction model that could be used to predict the success of a blended course, and perform on-going assessment for blended courses at any given time during the semester, with concurrent data at the time, so adjustment to deal with possible problems could be made to guarantee the high - quality implementation of the course prior to its conclusion. The second was to identify a way to utilize accessible data for achieving desired outcomes, especially when supplementary information beyond the data is unavailable. The innovative aspect of this study compared to others is:

1. Instead of treating individual students as subjects and collecting data from each to predict their individual learning outcomes, we used individual blended courses as the unit of study, with the data reflecting class performance from both students' and the instructor's perspectives and developed a model to predict the successful rate of the class.

2. We investigated how to employ such a model for ongoing assessment by leveraging the identified influential indicators, aiming to evaluate the efforts of both instructors and students throughout - the teaching learning process.

BACKGROUND INFORMATION REVIEW

For the study, this background information review includes: (a) the methods of examining blended courses and some difficulties when conducting such research; (b) the logistics to perform on-going assessment in blended courses, and (c) the relevant variables to be examined, including student-related, teacher-related, and course management related variables.

METHODS OF EXAMINING BLENDED COURSES

The design of a blended course can be based on different blended learning models (Soffer, Kahan, & Livne, 2017). For example, in a rotation model, students rotate between learning paths (e.g., between online learning and face-to-face learning) either on a fixed schedule or at the instructor's decision. The length of time, amount of learning contents, types of learning activities, criterion of evaluations, or location of learning differ from course to course (Baldwin & Yu-Hui, 2019). However, a flex model "allows for real-time changes in schedules to meet ever-changing student learning needs. The instructor even interacts with students face-to-face, his/her support is flexible and adaptive to individual student needs" (Beaver, Hallar, & Westmaas, 2014, p7). When conducting studies, the control of blended learning condition is always a challenge.

If a researcher uses students as the sample, it is easier to control the design components, as students in the same group would have the same blended learning condition. For example, researchers have identified attitudes toward blended learning, face-to-face support and digital literacy as the influential variables to predict learning performances (Wichadee, 2018), quality of learning system and online interaction as factors for differences between low and high group participations (Chang, et al., 2015), online or blended learning environment as the function of students' course satisfaction (Oshima et al., 2024), time spent on online learning or face-to-face learning as the function of learning achievement (Liu, 2017), and positive effects of institutional commitment on students persistence and success of online learning (Beck, H. P., & Milligan, M. (2014).

Comparatively, it is more difficult if a researcher uses blended courses as the sample to study the overall course learning outcomes, when some portion of off-line learning information is unavailable or uncertain (Ma, et al., 2015). Especially when data for blended learning courses were collected directly form the online learning management system that contained and only contained information of the online portion of the course, it is difficult to obtain the data of off-line portion from each blended course. An approach for such studies is to use the entire population for the study. For example, in a study to examine an assessment framework for blended courses in six universities, the authors collected data from each of the six universities that covered a total of 15128 blended courses and 7272 instructors. In this way, they analyzed the data and summarized the results that reflect the situation of all six universities as IT IS (Han, Wang, & Jiang, 2019). In current study, we adopted the same approach, used the data from ALL blended courses of one university to develop a model to predict overall learning outcomes from blended courses, and to perform on-going assessment.

LOGISTICS OF ON-GOING ASSESSMENT

This section presents a review about the logistics of on-going assessment for blended course. Such assessment has enabled educators to perform learning assessment or self-assessment in an ongoing pace at any given time of the blended course with in-coming data

(Liu & Gibson, 2018; Domun & Bahadur, 2014), to assess online course design, (Liu, & Chen, 2018; Liu & Gibson, 2018), and to improve the design and the operation of an online learning recommending system (Liu, Liang, & Li, 2017).

The term logistics originally was used in military, industry, or business, and was defined as "the careful organization of a complicated military, business, or other activity so that it happens in a successful and effective way to achieve the best outcomes" (Cambridge Dictionary, 2019). In the field of education, logistics was first summarized and defined as "dynamically coordinating the very basic and operational units, functions, or activities of a system to implement the best performance and produce expected products or outcomes" (Liu, Chen, & Li, 2019, p.35). According to this definition, the three key attributes of logistics were: the system, the basic units of the system, and the procedures to achieve the goal. When using the term logistics, researchers often started from these three key attributes: (a) determining the system – it could be the system of military, business, companies (Wu & Xu, 2024), or in education, a course, a program, or a university; (b) outlining the basic operational units, functions, tasks, or activities of the system and the rationale they are sorted into; and (c) determining the way of coordinating dynamically for best performance, which should follow the structure, functions, rules, or purposes of the system (Liu, Chen, & Li, 2019). In this study, the three attributes of logistics in the context of on-going assessment of blended courses were defined as in the following:

First, the blended courses was exactly the system. The function of this system was to deliver learning, including all materials, activities, tasks, structures, procedures, assessment of teaching and learning. Second, in the context of on-going assessment of the blended course, the basic units, operations, and activities were sorted into (a) the specific items to be assessed, (b) the basic method to perform the assessment, and (c) the on-going procedures. All variables we examined in this study were the basic units of the assessment. Finally, the most important was the way to coordinate and perform the on-going assessment, which led to the purposes of the study: (a) to develop a model to predict the success rate of a blended course, and (b) actually to explore an assessment model. Next, in reviewing the relevant variables, we were able to determine the variables to be examined in this study.

RELEVANT VARIABLES

Again, the function of the blended course system is to deliver and support learning, which involves the work of students, instructors, and institutional management (Jaggars, & Xu, 2016; Kearns, 2016; Wang & Han, 2017). Most blended learning studies in the field have explored variables related to these three types of work.

Literature has exhibited a variety of student-related variables such as student e-readiness, e-satisfaction and expectations (Ilgaz & Gülbahar, 2015), online interactions, self-perception and self-evaluation (Chen & Liu, 2018, 2019), cognitive processing (Chen & Pedersen, 2012), online communication skills and interactions (Diep, et al., 2017). Most instructor-related variables focused on assessment (Domun & Bahadur, 2014; Gay, 2016), course design (Chen & Liu, 2018), innovation of teaching methods (Kearns, 2016), and technology readiness (Martin, Budhrani, & Wang, 2019). In addition, Han and Ellis (2019) conducted a study examined about 30 mixed influential variables and established a set of models to predict blended learning. Beck and Milligan (2014) conducted a study with 831 online students and examined about 25 factors that related to the institutional commitment.

In most studies, the data were collected from the online learning management system where the portion of online learning was delivered. The web-log based data mostly were the frequency counts of certain activities or performance, for example, the total number of student discussion posts, the total number of assignments students submitted or the instructor graded, or the amount of course resources provided by the instructor (Ma, et al., 2015). In this study we examined the similar student-related, instructor-related, and course-related variables, and explored the extent to which such data could be used to predict learning outcomes.

CONSISTENCE ACROSS DISCIPLINES

When conducting studies using all the courses in a university as in current study, one concern was to what extent a model developed with the entire population could reflect the specifics cross disciplines. From the perspectives of education in general, instructors' work and students' efforts would always contribute to the learning outcomes. However in different disciplines, the nature of knowledge, the methods to deliver instructions, different learning styles, and the technology or media tools used could be very different, for example, in language learning (Chakowa, 2018), mathematics learning (Xueli et al., 2025), science learning (Canbulat & Uzun, 2024), and engineering learning (Durak, 2024) . Even the value of a given variable (e.g., the number of discussion posts) may have different indications in different disciplines (McPherson, 2014).

The purpose to develop the predicting models was to prepare educators to for on-going assessment. In this study, we explored the common features among all the blended courses in a university as well as unique features of courses in liberal art colleges and in STEM colleges of the university.

RESEARCH QUESTIONS OF THE STUDY

For the purposes of the study, the following research questions were examined:

1. Can the successful rate of a blended course be predicted by any of the student-related, teacher-related, or course-related variables, based on the data from all the blended courses in the university?
2. If yes, which of those variables are direct influential variables, and which are indirect influential variables?
3. Is the overall predicting model based on the data of the entire university consistent with the two models based on data from liberal art colleges, and STEM colleges?

METHODOLOGY

SAMPLE AND SETTINGS

The sample of this study was 2238 blended courses offered from 24 colleges at a university in an eastern province of China. Data were collected at the end of spring semester of 2018 from the learning management system of the university. The overall student enrolment of the 2238 courses was 209,233. This enrolment number was not necessary the number of students in the university, as most students may have registered for more than one class.

The courses were offered in a variety of areas from these colleges: Foreign Languages (165), Literacy and News Media (87), Law (93), Political Sciences (32), Business and Management (149), Economics (77), Agriculture and Food Sciences (89), Career and Innovation (31), Mathematics and Statistics (115), Physical Optoelectronics (48), Life Sciences (44), Transportation and Vehicle Engineering (89), Chemical Industry (113), Construction (133), Materials Science and Engineering (51), Electronics Engineering (139), Computer Science and Engineering (174), Resources and Environmental Sciences (61), Textile (35), Sports (118), Art (112), and Music (123). In addition, 26 courses were offered from "others" including university Libraries, Student Management Department, and campus Police Department.

The online learning management system used in this university was a system developed by Tsinghua University, China and has been adopted in more than four hundred universities and colleges in China for their online or blended courses. The system provided supporting tools for course administration (e.g., course introduction, and course announcement), course contents delivery (e.g., media tools and e-books), interaction tools (e.g., discussion board and message tool), and assessment tools (e.g., course assignment, test, or questionnaire). From those system supporting tools, we were able to locate and download the information for this study.

All the courses were considered blended courses with online portion managed and delivered through this online learning management system, and face-to-face portion managed in classrooms. The frequencies of all the students' online learning activities and the teachers' online instructional activities were recorded in the system.

DATA COLLECTION, CODING, AND MEASUREMENT

Data were collected at the end of the spring semester of 2018 after the class grades were posted by the instructors. From the university online learning management system we collected course information and sorted them into student-related, teacher-related, and course-related variables. As the purpose of the study was to develop a model that could be used to perform on-going assessment of a course, we collected all the information we could possibly obtained, and they were the variables often studied in the literature as well (Falakmasir & Habibi, 2019; Ma, et al. 2015; Jiang et al., 2023; Gong, 2024). Totally 24 variables were included:

Student-Related Variables (6):

- S1. Student Logins
- S2. Assignments Submitted
- S3. Tests Submitted
- S4. Discussion Responses (in Student Discussion Forums)
- S5. Discussion Topic Posts (in Student Discussion Forums)
- S6. Course Materials Reviewed

Teacher-Related Variables (14):

- T1. Teacher Logins
- T2. Announcements Made
- T3. Questionnaires Conducted
- T4. Tests Created
- T5. Exploring-Themes Initiated
- T6. Tests Posted
- T7. Tests Grated
- T8. T-Discussion Posted (in Teacher Discussion Forums)
- T9. T-Discussion Topics Initiated (in Teacher Discussion Forums)
- T10. Common Problems Identified/Posted
- T11. Course Sessions Created
- T12. Course Session Videos Posted
- T13. Assignments Created/Posted
- T14. Course Resources Created

Course-Related Variables (4):

- C1. Total Visits
- C2. Course Session Resources
- C3. Course Discussion Posts
- C4. Course Discussion Topics Posted

The coding for the 6 student-related variables, 14 teacher-related variables, and the 4 course-related variables was simply taking from the logs of the university online learning management system, using the frequency counts for each variable as the coding values. For example, in one class, if students totally submitted 125 assignments, the variable *assignment submitted* was coded as 125. Again, for the purpose of using the information directly from the system to conduct on-going assessment, we used all the raw values as they are for the analysis of this study.

The measurement of learning outcomes in most student-sampled studies was individual student test scores. This study was a course-sampled study where an individual blended course was a unit. The response variable for this study was *course successful rate*. For each course, we calculated the percentage of students who received the grade points, based on a 100 points scale, at four levels: 90 points and above (grad of A), 76 to 89 points (grade of B), 60 to 75 points (grade of C), and 59 points and lower (not pass). For example, in a course of 50 students, if 8 students received the 90 points or more, then the rate of A for that class would be 8/50 = 16%.

To determine which level could be used to represent a general *successful rate* for a course. We did a descriptive review on each level, they all had some skewed trend. We decided to use the range of B and above. We combined the levels of A and B to create a new level of "76 points and above" and use it as the *course successful rate*. In general, the B-and-above population has been a commonly accepted average representation of a course (Liu & Maddux, 2005).

DATA ANALYSIS AND RESULTS

To answer the research questions, multiple regression analyses were conducted. First, three initial predicting models were to be developed: (a) using the data of all blended courses in the university for Model 1, (b) using the data from liberal art colleges of the university for Model 2, and (c) using the data from STEM colleges in the university for Model 3. Any student-related, teacher-related, or course-related variables that significantly contributed to a model, and did not violate the multi-nonlinearity requirements were included in the model.

Second, the direct and indirect influential variables were determined with this reasoning: if A is influenced by B and B is influenced by C, then B influences A directly, C influences A indirectly (via B), and B is the intermediate variable between A and C (Liu, Maddux, & Johnson, 2004).

Third, the consistence among the models in this study was evaluated with two indicators: (a) the amount of common direct or indirect influential variables that was shared by the models, and (b) the pattern that the student-related variables and teacher-related variables were distributed in the models.

The Pearson correlation analysis between all the predictor variables and the Course Successful Rate was conducted at the beginning, and all the correlations were positive.

THE OVERALL PREDICTING MODEL (MODEL 1)

In the initial analysis, all 24 variables were used as the predictor variables. The response variable was *Course Successful Rate* at the B-and-above level (which is the percentage of students in a class who earned a grade of 76 points and above). Multiple linear regression analysis was performed. The linear model was significant ($F_{(4, 2237)} = 2.694$, $p = .029$, $R^2 = .015$). Three student-related variables (Student Logins, Student Assignment Submitted, and Course Materials Reviewed) and one teacher-related variable (Assignments Posted by the teacher) were significant to the model (see Table 1). Multi-collinearity statistics for the four variables were also examined and were not problematic. Variables with the Tolerance values less than 0.1 were not included into the model. The VIF (Variance Inflation Factors) values showed some slight to moderate correlations but were within the acceptable range: a VIF value of 1 indicates no correlation, 5 indicates moderate correlation, larger than 5 till 10 indicates high correlation (Cohen, et al., 2003, p. 423;

Keith, 2006, p. 201). The Course Successful Rate could be directly predicted by these four variables.

Table 1. *Overall model 1*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	0.623	66.56	<.001		
(S1) Student logins	0.109	2.705	.007	.11	3.135
(S2) Assignment Submitted	-0.791	-2.479	.013	.10	1.937
(S6) Review Course Materials	-0.767	-1.768	.026	.13	3.749
(T13) Assignments Posted	0.05	1.949	.006	.38	2.604
Dependent Variable: Course Successful Rate (above 76)					
$F_{(4, 2237)}$ =2.694, p = .029, R^2 = .015					

However, this four-variable model seemed not a complete representation of the data. Then, the next step of exploration was to examine if each of these four variables could be predicted by any combination of the rest of the 24 variables. Four sub-models were examined next.

Model 1-A

In this analysis, the response variable was Student Logins, and the rest in the 24 variables were used as predictor variables. The linear model was significant ($F_{(22, 2237)}$ =301.486, p < .001, R^2 = .96). One student-related variables (Discussion Responses) and one teacher-related variable (Teacher Logins) were significant to the model (see Table 2). Multi-collinearity statistics were acceptable as well. The frequency of Student Logins could be predicted by the frequency of a teacher's login times and the numbers of discussion responses the student posted to the course. This model seemed not very convincing, but it did indicated that these two variables (Teacher Logins, and student Discussion Responses) indirectly influenced the Course Successful Rate, via the intermediate variable Student Logins.

Table 2. *Overall model 1-A*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	-4.004	-.025			
(T1) Teacher Logins	0.977	-16.922	<.001	.218	2.590
(S4) Discussion Responses	0.201	4.397	<.001	.107	3.021
Dependent Variable: (S1) Student Logins					
$F_{(22, 2237)}$ =301.486, p < .001, R^2 = .96			*VIF moderately correlated		

Model 1-B

Nest, we used student Assignment Submitted as the response variable, and the rest in the 24 variables were used as predictor variables. The linear model was significant ($F_{(22, 2237)}$ =2108.02, p < .001, R^2 = .95). Three student-related variables (Tests Submitted, Discussion Responses Posted, and Discussion Topic Posted) and two teacher-related variables (Questionnaires Conducted, and Tests Graded) were significant to the model (see Table 3). Multi-collinearity statistics were acceptable as well. The frequency of student Assignment Submitted could be predicted by the five variables in this model. These five variables indirectly influenced the Course Successful Rate, via the intermediate variable student Assignment Submitted, and they were the indirect influential variables to Course Successful Rate in the overall model.

Table 3. *Overall model 1-B*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	-18.544	66.56	.001		

(S3) Tests Submitted	-1.158	-12.665	<.001	.139	1.174
(S4) Discussion Responses	-0.217	-12.113	<.001	.182	2.216
(S5) Discussion Topic Posts	0.586	9.768	<.001	.212	1.474
(T3) Questionnaires Conducted	-18.170	-4.344	<.001	.661	1.513
(T7) Tests Graded	0.391	3.168	.002	.319	3.138
Dependent Variable: (S2) Assignment Submitted					
$F_{(22, 2237)}$ =2108.02, p < .001, R^2 = .95					

Model 1-C

Then, we used the third predictor variable in the overall model, student Course Materials Reviewed as the response variable for this sub-model, and the rest in the 24 variables were used as predictor variables. The linear model was significant ($F_{(22, 2237)}$ =1283.628, p < .001, R^2 = .927). Interestingly, in this model, eight teacher-related variables (Teacher Logins, Announcements Made, Questionnaires Conducted, Test Graded, teacher Discussion Topic Posted, Course Sessions Created, Course Videos Posted, and Course Resources Created) and one student-related variable (Tests Submitted) were significant to the model (see Table 4). Multi-collinearity statistics for all nine variables were examined and were not problematic. The frequency of students Course Materials Reviewed could be predicted by the nine variables in this model. These nine variables indirectly influenced the Course Successful Rate, via the intermediate variable student Course Materials Reviewed, and they were the indirect influential variables to the overall model.

Table 4. *Overall model 1-C*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	128.584	3.051	.002		
(T1) Teacher Logins	13.748	9.023	<.001	.227	3.411
(T2) Announcements Made	41.595	2.286	.022	.452	2.210
(T3) Questionnaires Conducted	-108.284	-5.548	<.001	.664	1.505
(T7) Tests Graded	-3.391	-3.527	<.001	.319	3.135
(T9) Discussion Topic Posts	-76.712	-4.607	<.001	.610	1.639
(T11) Course Sessions Created	-56.028	2.592	.01	.595	1.680
(T12) Course Video Posted	-33.735	-2.536	.011	.582	1.719
(T14) Course Resources Created	5.124	4.811	<.001	.721	1.387
(S3) Test Submitted	-0.434	-4.324	<.001	.131	3.629
Dependent Variable: (S6) Review Course Materials					
$F_{(22, 2237)}$ =1283.628, p < .001, R^2 = .927					

Model 1-D

Finally, we used the last predictor variable in the main model, Assignment Posted by teachers, as the response variable for this sub-model, and the rest in the 24 variables as predictor variables. The linear model was significant ($F_{(22, 2237)}$ =161.456, p < .001, R^2 = .616). Similar with Model 1-C, in this model, six teacher-related variables (Teacher Logins, Announcements Made, Test Created, Test Graded, teacher Discussion Topic Posted, and Common Problems Posted by teachers) and one student-related variable (Tests Submitted) and were significant to the model (see Table 5). Multi-collinearity statistics were acceptable. The frequency of teachers posted assignment could be predicted by the seven variables. That is, the seven variables indirectly influenced the Course Successful Rate, via the intermediate variable student Assignment Posted by teachers, and they were the indirect influential variables to the main model.

Table 5. *Overall model 1-D*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	0.402	5.713	<.001		
(T1) Teacher Logins	0.041	16.726	<.001	.246	3.710
(T2) Announcements Made	0.178	5.876	<.001	.458	2.181
(T4) Test Created	0.709	3.853	<.001	.676	1.479
(T7) Tests Graded	-0.701	-4.627	<.001	.320	3.122
(T9) Discussion Topic Posts	0.193	6.929	<.001	.618	1.619
(T10) Common Problems Posted	-0.119	-3.111	.002	.584	1.713
(S3) Test Submitted	0.010	2.109	.035	.130	3.678
Dependent Variable: (T13) Assignments Posted					
$F_{(22, 2237)}$ =161.456, $p < .001$, $R^2 = .616$					

In summary, the main model developed with all courses in the university showed four direct influential variables (the four variables from main Model 1), and a total of 13 common indirect influential variables. We counted the number of common variables in the four sub-models. Some variable like Test Graded appeared in three sub-models, but we only counted it once.

THE LIBERAL ART COURSES PREDICTING MODEL (MODEL 2)

Next, to explore the blended courses in different disciplines, we examined the courses in liberal art colleges in the university, including the colleges of Foreign Languages, Literacy and News Media, Law, Political Sciences, and History. Totally 383 blended courses were analyzed to determine which student-related, teacher-related, or course-related variables could predict the Course Successful Rate, and to evaluate if this model is consistent with the main model of the university.

In this analysis, all 24 variables were used as the predictor variables, and the Course Successful Rate as the response variable. The linear model was significant ($F_{(23, 382)}$ = 301.486, $p = .029$, $R^2 = .117$). Two student-related variables (Student Logins, and Course Materials Reviewed) and one teacher-related variable (Course Session Created) were significant to the model (see Table 6). Multi-collinearity statistics for the three variables were also examined and were not problematic. The Course Successful Rate of liberal art courses could be directly predicted by these three variables.

Table 6. *Liberal arts model 2*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	0.743	36.525	<.001		
(T11) Course Sessions Created	-0.890	-12.531	.012	.369	2.713
(S6) Course Materials Reviewed	-1.827	-2.381	.018	.121	3.152
(S1) Student Logins	2.582	2.759	.006	.103	2.653
Dependent Variable: Course Successful Rate (above 76)					
$F_{(23, 382)}$ = 301.486, $p = .029$, $R^2 = .117$					

Next, two sub-models were examined to determine if each of these three variables could be predicted by any combination of the rest in the 24 variables).

Model 2-A

In this analysis, Course Sessions Created by the instructor was used as the response variable, and the rest in the 24 variables were used as predictor variables. The linear model was significant ($F_{(22, 382)}$ = 28.038, $p < .001$, $R^2 = .631$). Only two teacher-related variables (Exploring Themes Initiated and Course Resources Created) were significant to the model (see Table 7). Multi-collinearity statistics were acceptable. The frequency of Course Sessions Created by the instructor could be predicted by these two variables. Therefore, these two variables could be considered the indirect influential variables to the main liberal art model, as they influenced the Course Successful Rate indirectly via Course Session Created.

Table 7. *Liberal arts model 2-A*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	-0.018	-0.601			
(T5) Exploring Themes Initiated	1.803	9.410	<.001	.765	1.307
(T14) Course Resources Created	0.006	3.442	.001	.205	3.887
Dependent Variable: (T11) Course Sessions Posted					
$F_{(22, 382)} = 28.038, p < .001, R^2 = .631$					

Model 2-B

In the next analysis, Course Materials Reviewed by students was used as the response variable, and the rest in the 24 variables were used as predictor variables. The linear model was significant ($F_{(22, 382)} = 595.585, p < .001, R^2 = .973$). Interestingly, all the significant variables in this model were teacher-related variables (Announcements Made, Questionnaires Conducted, Test Created, Discussion Posts, Discussion Topic Posts, Common Problems Posted; and Course Resources Created). All these seven variables significantly influenced the Course Materials Reviewed by students (See Table 8), and they were considered the indirect influential variables to the main liberal art model, as they influenced the Course Successful Rate indirectly via Course Materials Reviewed.

Table 8. *Liberal arts model 2-B*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	43.396	.334			
(T2) Announcements Made	-174.034	-2.130	.034	.320	3.121
(T3) Questionnaires Conducted	-172.464	-2.357	.019	.403	2.480
(T4) Tests Created	-196.520	-2.028	.043	.108	2.766
(T8) Discussion Posts	60.912	4.464	<.001	.393	2.547
(T9) Discussion Topic Posts	-124.088	-3.945	<.001	.521	1.921
(T10) Common Problems Posted	-155.875	-1.966	.049	.314	3.184
(T14) Course Resources Created	-27.988	-3.391	.011	.204	2.892
Dependent Variable: (S6) Course Materials Reviewed					
$F_{(22, 382)} = 595.585, p < .001, R^2 = .973$					

The analysis on the other variable in the liberal art main model was Student Logins. No variables found were significant to predict Student Logins. So, the liberal art model remained with the two sub-models.

THE STEM COURSES PREDICTING MODELS (MODEL 3 AND 3A)

The last model examined was based on courses from STEM colleges in the university, including the colleges of Transportation and Vehicle Engineering, Chemical Industry, Construction, Mechanical Engineering, Materials Science and Engineering, Electronics Engineering, Computer Science and Engineering, and Resources and Environments. A total of 1220 blended courses were analyzed to determine which student-related, teacher-related, or course-related variables could predict the Course Successful Rate, and to evaluate if this model is consistent with the overall model of the university.

In this analysis, all 24 variables were used as the predictor variables, and the Course Successful Rate as the response variable. The linear model was significant ($F_{(22,\ 1219)}$ = 1.593, p < .04, R^2 = .028). Only one teacher-related variable (Assignment Posted) was significant to the model (see Table 9). That is, for all the engineering blended courses, this is the only variable that directly influenced the Course Successful Rate.

Table 9. *STEM model 3*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	0.515	51.523	<.001		
(T13) Assignment Posted	0.010	2.988	.003	.366	2.730
Dependent Variable: Course Successful Rate (above 76)					
$F_{(22,\ 1219)}$ = 1.593, p < .04, R^2 = .028					

However, when continued examining the sub-model (Model 3-A), using Assignment Posted as the response variable and the rest in the 24 variables as the predictor variables, we found that the linear model was significant ($F_{(22,\ 1219)}$ = 98.704, p < .001, R^2 = .634), and 10 variables were significant (see Table 10), including five teacher-related variables (Teacher Logins, Announcements Made, Tests Graded, Common Problems Posted, and Course Resources Created), three student-related variables (Assignments Submitted, Discussion Topic Posts, and Course Materials Reviewed), and two course-related variables (Course Total Visits, and Course Session Resources). These 10 variables were considered to have indirect influences to Course Successful Rate via Assignments Posted.

Table 10. *STEM model 3-A*

Model	Unstandardized B	t	P	Tolerance	VIF
Constant	.340	4.156	<.001		
(T1) Teacher Logins	.048	13.389	<.001	.160	3.608
(T2) Announcements Made	.254	6.323	<.001	.382	2.620
(T7) Tests Graded	-.109	-3.173	.002	.639	1.565
(T10) Common Problems Posted	-.139	-2.645	.008	.555	1.800
(T14) Course Resources Created	-.505	-2.200	.028	.684	1.462
(S2) Assignments Submitted	.810	17.091	<.001	.104	2.951
(S5) Discussion Topic Posts	-.010	-2.926	.003	.287	3.490
(S6) Course Materials Review	.120	3.925	<.001	.528	1.993
(C1) Course Total Visits	0.442	3.035	.002	.484	2.064
(C2) Course Session Resources	-.731	-2.237	.025	.472	2.121
Dependent Variable: (T13) Assignment Posted					
$F_{(22,\ 1219)}$ = 98.704, p < .001, R^2 = .634					

SUMMARY OF THE RESULTS

ANSWERS TO RESEARCH QUESTIONS ONE AND TWO

In summary, the results from the overall main model (Model 1) and the four sub-models (Models 1A, 1B, 1C, and 1D) answered the first two research questions. Using the data from all 2238 blended courses, an initial prediction model was developed. The Course Successful Rate can be predicted by a linear combination of Student Logins, student Assignments Submitted, Course Materials Reviewed by students, and the frequencies of Assignments Posted by the instructor. These four variables were the direct influential variables to a course's successful rate. Also, as shown in Figure 1, three student-related variables and 10 teacher-related variables were identified as the indirect influential variables to the Course Successful Rate.

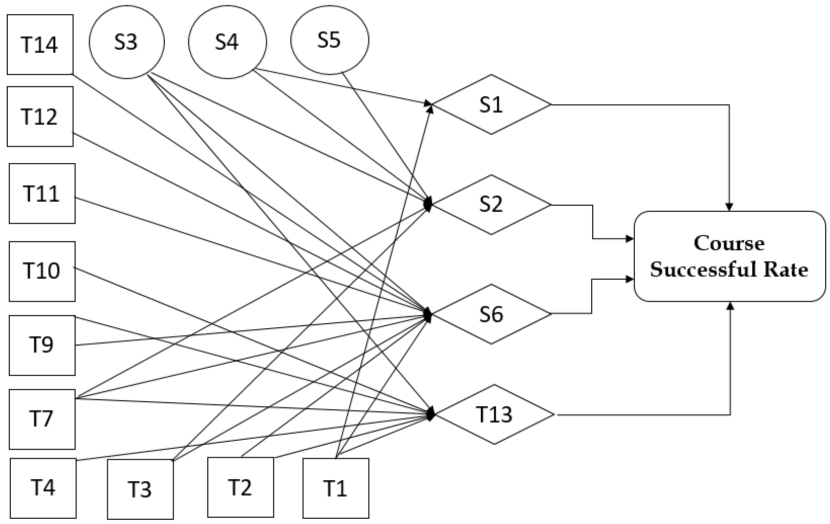

*Figure 1***.** The Direct and Indirect Variables in Model 1 (N=2238 Blended Courses)

The results were not surprising. According to the two layers of the model, students' efforts are critical to the course success as three out of four direct influential variables were student-related variables, while the teacher's efforts were the same important as10 out of the 13 indirect influential variables were teacher-related. They influenced the Course Successful Rate indirectly via student-related variables.

ANSWERS TO RESEARCH QUESTION THREE

The purpose to develop the predicting models was to prepare educators for ob-going assessment to the blended courses whose online portion was delivered through the learning management system. With the diversity of disciplines among the courses, we also needed to know the extent to which the overall model (the Model 1) could (a) represent the general or common features of courses in different disciplines, and (b) was consistent with the models based on courses in liberal art colleges (Model 2), and based on courses in STEM colleges (Model 3). The consistence of the models was evaluated from two perspectives: (a) the amount of common direct or indirect influential variables that was shared by the models, and (b) the pattern of student-related variables and teacher-related variables that was distributed in the models.

First, screening the direct and indirect variables in the three models (See Table 11), we found that Model 2 (based on liberal art courses) shared two direct variables (Course Materials Reviewed and Student Logins) and six common indirect variables (those with * sign in Table 11) with the overall model, and Model 3 (based on STEM courses) shared its one direct variable (Assignments Posted) and six common indirect variables (those with * sign in Table 11) with the overall model. 75% of common indirect variables in Model 2 (six out of eight) and 60% of the common indirect variables in Model 3(six out of 10) were shared with the overall model.

Table 11. *Summary of direct and indirect influential variables*

Response Variables	← Direct Influential Vs	← Indirect Influential Vs	{Common Indirect Vs}
Model 1 All Courses	(S1) Student Logins	(T1), (S4)	(T1), (T2), (T3), (T4), (T7), (T9),

N = 2238 *(Y) =* *Course Successful Rate*	(S2) Assignment Submitted	(T3), (T7), (S3), (S4), (S5)	(T10), (T11), (T12), (T14) (S3), (S4), (S5)
	(S6) Review Course Materials	(T1), (T2), (T3), (T7), (T9), (T11), (T12), (T14), (S3)	
	(T13) Assignments Posted	(T1), (T2), (T4), (T7), (T9), (T10), (S3)	
Model 2 Liberal Arts Courses *N* = 383 *(Y) =* *Course Successful Rate*	(T11) Course Session Posted	(T5), (T14)	***(T2), *(T3), *(T4),*** (T5), (T8), ****(T9),*** ***(T10), *(T14),***
	(S6) Review Course Materials	(T2), (T3), (T4), (T8), (T9), (T10), (T14),	
	(S1) Student Logins		
Model 3 STEM Courses *N* = 1220 *(Y) =* *Course Successful Rate*	(T13) Assignment Posted	(T1), (T2), (T7), (T10), (T14), (S2), (S5), (S6) (C1), (C2)	***(T1), *(T2), *(T7),*** ***(T10), *(T14),*** (S2), ****(S5),*** *(S6)* (C1), (C2)

(*) – Common indirect variables shared with Model 1.

Second, revealed from the model pattern review, one feature that was common in the three models was that they only had a few direct influential variables (four, thee, and one respectively for the overall model, liberal art model and STEM model), but more indirect influential variables (13, 8, and 10 respectively for the three models). This indicated that in all three models a relatively large portion of influencing could be sourced from the indirect influences. Another common feature in the three models was the distribution of the student-related variables and teacher-related variables: most teacher-related variables were indirect influential variables, and they influenced the Course Successful Rate via student-related variables. One exception was in the STEM model, since it only had one teacher-related variable (Assignment Posted) as the direct variable. In the overall model, 77% (10 out of 13) common indirect variables were teacher-related, and 100% (all eight) and 50% (five out of 10) common indirect variables were teacher-related variables in liberal art model and STEM model respectively.

The overall model in general could be considered consistent with the other two models, where different attentions on certain variables may need when adopting them for on-going assessment in courses from different disciplines. Next, we will discuss the logistics of using these models to perform on-going assessment and suggest some methods.

ON-GOING ASSESSMENT FOR BLENDED COURSES

THE PREDICTING MODELS AND THE LOGISTICS OF ON-GOING ASSESSMENT

With the initial predicting models, performing on-going assessment in blended courses becomes possible. In the context of this study, on-going assessment is to perform learning assessment or self-assessment at any given time of the blended course with in-coming data (Liu & Gibson, 2018; Domun & Bahadur, 2014), to assess course design, (Liu, & Chen, 2018; Liu & Gibson, 2018), online course performance including teacher's efforts and students efforts, and the likelihood of course success, with a pre-set course successful rate.

Derived from the experiences of Liu and Gibson (2018), Figure 2 illustrates the procedures of on-going assessment. With the predicting models, the logistics to conduct such assessment for a blended course can be described in operations. First, all the information reflected by all variables can be collected from the online learning management system, as we did in this study. They are the measurable basic units, operations, or activities of a blended course, and the basic units and indicators to perform on-going assessment. Second, the procedures and methods to conduct such assessment can be performed from two dimensions: (a) the operation procedures demonstrated in Figure 2, and (b) evaluating the performance on each of the indicators that can be calculated or presented with the predicting models.

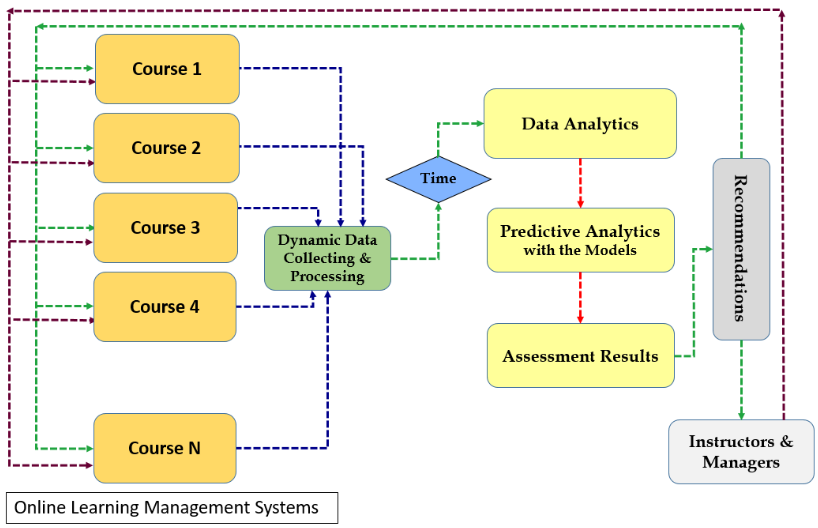

Figure 2. On-going Assessment of the Blended Courses

Figure 2 demonstrates an on-going assessment model, it works with an operation cycle through each part of the model:

1. Courses are operated in the learning management system;
2. Data from each course are collected and processed;
3. Data analytics are conducted with the predicting models;
4. Assessment results on the performance efforts are generated, issues or problems if any would be revealed;
5. Recommendations are made;
6. Recommendations are sent to the instructor as well as to each course (if students can assess),
7. The instructor at this point can make any adjustment on the teaching and learning to improve the course.

Also, it works dynamically when adding a variable Time as a condition variable into the cycle of operations (Liu, Chen, & Li, 2019). At a given time, the performance data can be processed with the predicting models, identifying the performance efforts from both students and the instructor, and then generating their performance effect on course success with the predicting models. The assessment can be performed with overall model and specific models for specific courses in different disciplines.

The Index of Instructor's Efforts

As shown in the results, teacher-related variables are the main sources of the influences on a course' success. The alert is: what measurements specifically can be used to evaluate the instructor's efforts? The teacher-related variables in this study may be sorted into several factors, for example, design related, content delivery related, communication and interaction related, assessment related, motivation related, or self-regulation related. They can be used to generate an index of the instructor's efforts. To generate such an index, we expect to work on data from numerous of courses. We may look at the weight of each factor, the variation of each factor for courses in different disciplines, or their contribution to the likelihood of a success course (Keith, 2006; Mertler & Reinhart, 2017; Worthen, et al., 1999; Ysseldyke, 1998). The methods are to be explored in our further studies.

If the calculation of instructor's efforts is developed, and is imported into the prediction model, then, when the on-going assessment model runs, the report on instructor's efforts will be generated. From the perspectives of both professional assessment and instructor's self-assessment, this information will be of great reference to improve the teaching and learning in the blended courses or other online courses.

DISCUSSIONS AND CONCLUSIONS

In summary, this study has analyzed 2,238 blended courses incorporating 24 predictor variables and established an initial predictive model. Overall, four direct influential variables and 13 indirect influential variables (comprising three student - related variables and 10 teacher - related variables) were identified as significantly impacting the success rate of blended courses. Additionally, two specialized models were developed based on courses from liberal arts colleges and STEM colleges respectively. The consistency between the overarching model and the two specific models is predominantly reflected in two aspects: (a) analogous model structures, and (b) the predominant influence stemming from teacher - related variables. Furthermore, this study has delved into the application of these models for ongoing assessment. The findings lead to the following conclusions.

OPEN-ENDED APPROACH OF THE ASSESSMENT

This study utilized the entire student population of a university as the sample cohort. We are confident that the models accurately reflect the university's objective. However, blended courses are delivered through diverse models (Beaver et al., 2014), encompassing both online and offline components (Margulieux et al., 2016; Owston & York, 2018). When research focuses solely on online data, a common follow - up inquiry arises: what proportion of a course's success rate is attributable to offline work, which is not captured by online learning management systems? Currently, we acknowledge that providing a precise answer to this question is challenging.

Nevertheless, our argument hinges on maintaining the offline efforts of students and instructors at the same level as observed during this particular semester. Under this assumption, we assert that our results and findings hold true, which is why we designate our model as "initial." When employing this model to forecast future performance—a primary objective of developing such models—we will adopt an open - ended assessment approach (Liu & Maddux, 2010). Initially, we can utilize the direct and indirect variables identified in this study to conduct analogous analyses and model development, incorporating a continual variable "Time" to define time points and determine whether consistent models can be achieved. Subsequently, leveraging these initial models, advanced data mining analyses can be performed using machine learning and deep learning techniques to enhance model accuracy. These data analytics procedures will persist throughout the semester, enabling assessments at any given time point.

The open - ended approach is one of the four characteristics of dynamic design (nonlinear, multiple - dimensional, process - based, and open - ended) proposed by Liu and Maddux (2005). It has been shown to positively impact learning outcomes and the quality of learning application design (Liu & Maddux, 2010). Within the blended learning context outlined in this study, the open - ended assessment approach is considered suitable and will be further explored in subsequent research.

INSTRUCTORS' EFFORT MATTERS

Another significant implication drawn from the results is the crucial role of instructors' efforts. As demonstrated by the findings, students' efforts exert a direct influence on the success rate of a course; however, these efforts are themselves shaped by the instructors' input. This chain - reaction - like finding echoes existing literature.

For instance, Liu and Maddux (2005) investigated the link between students' course evaluations and instructors' efforts in course design. Their study revealed that the likelihood of students assigning higher or more positive ratings to a course could be predicted by the extent to which instructors integrated dynamic design elements into the course. Chen and Liu (2018) found in their research that instructors' self - assessment, facilitated by interactions with students in online courses, enabled the identification of potential student issues and difficulties, thereby enhancing learning outcomes. The findings from this study align with and provide further support for these established research conclusions.

Finally, despite the absence of offline information in the analysis, the consistency across the models underscores the models' priorities. Assuming that the offline efforts of both students and instructors remain constant throughout the course, the models reliably indicate that instructors' efforts serve as the principal influence on the course success rate.

LIMITATIONS AND FURTHER STUDIES

One limitation of this study was that the sample was from one university in China. Although this study reflected the real-world situation of the blended courses offered in this particularly university, the results and findings may not be generated to a larger population of higher education in China. In addition, as the learning environment, pedagogical framework, educational emphases and expectations, and student population were featured with Chinese culture. We may not be able to adopt the results and findings in a global range.

Another limitation was the literature review on the variables we used in the study. As we decided to use all the information that we could obtain from the learning management system, we did not review those variables one by one to provide the rationales for each.

Based on the initial research findings, we foresee a research agenda in the near future: (a) to develop the index of instructor's efforts, (b) to examine the weight of offline and online portion in blended courses, (c) to explore the models with course in other disciplines, like sports, music, and arts (they were very different disciplines, but when mixed in this model, they seemed to have the same features as in others), (d) to employ other data mining methods for the model development, (e) to continue explore the chain-effect of the influences by teachers, and (f) to study the differences with nation-wide data in China, or data from universities in other countries.

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