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Remedial education for high-risk university freshmen – the case of a university of technology in Taiwan

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ABSTRACT

Potential high-risk freshmen for three core courses (BasicMath, Calculus, and Computing) in the university were identified based on the "College Students' Adjustment Check List (CSACL)" data available with the Student Development Centre in the Office of Students' Affairs of the university. The study demonstrates that to ameliorate the problem of unpreparedness of freshmen, to check failure rates, and efficient use of limited resources, an effective remedial system could be developed by the combined inputs from the Office of Students' Affairs, Computer Centre, Academic Affairs, and the Institutional Research. Our study corroborates the findings of other researchers that gender, teacher, department, high school performance, enrolment channel, and loads during remedial course influence the learning outcome. Also, it was found that the use of multi-evaluation approaches in different enrolment channels can attain higher retention rates.

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Remedial education; CSACL; high-risk freshmen

Introduction

The transition of freshmen to university education is quite challenging and has been a cause of concern for students, parents, and educationists in many societies. It is generally recognized that some freshmen when moving to university do not have the necessary skills for competent participation in the core subjects. For their integration and successful completion of their educational goals, it is important to identify such potentially high-risk or low achievers so that failure rates can be checked. Remedial education also known as compensatory tutoring or preparatory assistance plays an important role to achieve expected competencies in core subjects and academic up-gradation of underprepared university freshmen.

There are several reports on the application of remedial education in different countries, especially in the USA. According to Weissman, Bulakowski, and Jumisko (1997, p. 74), a remedial programme "enables students to gain the skills necessary to complete college-level courses and academic programs successfully". This remedial assistance is primarily intended for potentially high-risk or low-achieving freshmen. It is generally recognized among the educationists and researchers that high-risk freshmen immensely benefit from such assistance (Hoyt & Sorensen, 1999; Kirst, 1998; Moloney, 1996; Sandham,

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1998). It has been reported that Maths and English remediation decreased the probability of students dropping out of university and increased the likelihood of earning a degree (Bettinger & Long 2009). Additional evidence supporting the effectiveness of remedial education was provided by Lesik (2006) who showed that participation in a developmental mathematics programme increased the likelihood of successful completion of a college-level Maths course on the first entry.

In a study carried out at the United States International University in Kenya, it was found that the English remedial course provided to unprepared students was useful and uplifted the proficiencies of students after the remediation (Luoch, 2014). In a more recent report from the USA, it was shown that college readiness for graduating high school students especially for Maths differed across gender and socioeconomic backgrounds and needed an academic support from the university (Atuahene & Russell, 2016). However, remedial education lays an extra financial burden on students and parents and exerts pressure on the limited resources available to an academic institution. Therefore, it is imperative that given the differential cultural background and prevailing variable local factors, and differing opinions on the subject, each academic institution carries out its own research to figure out the extent of the problem, so that necessary remedial steps could be taken and available resources could be used in the most efficient manner.

Since 2005, the Ministry of Education (MOE) in Taiwan offers financial subsidy under the "Teaching Excellence Program". The expenditure towards remedial education under this programme is supported by the Taiwan government, and there are no financial constraints for low achievers and their guardians. The MOE and universities both play pivotal roles in ensuring that opportunities for quality education are made accessible to students who are in need financially. This helps students to be more stable in both learning and retention. Therefore, remediation is a necessary support for unprepared students in higher education in Taiwan. However, only 30–40% of universities in Taiwan pass the eligibility criterion for the subsidy and qualify to receive remedial education funds. The threshold of application is set to alarm and redeem the low achievers in order to improve their learning ability through quality control. In an independent study, Xiao (2011) found that the remedial assistance programme has a positive impact and helps low achievers to improve their performance in universities. Our university has qualified to receive the remedial financial support. However, it is important to utilize the limited resource in the most efficient manner.

Since 2014, the MOE has been shaping the field of Institutional Research (IR) in higher educational institutions. It focuses on student learning outcomes based on data-driven research to direct policy-making and institutional resource management for self-evaluation. Therefore, the office of "Institutional Research" in the university carries out research to analyse the financial and academic aid policies of remediation to help the decision makers.

The study aims to identify the extent of potentially high-risk freshmen for remedial measures so that students can avoid failure and achieve their educational goals. Contrary to other researchers, we used the College Students' Adjustment Check List (CSACL) for early detection of a high-risk group. In this study, we focused on the freshmen in the Science & Engineering college who enrolled in BasicMath, Calculus, and Computing in the first year, and explored the effect of remedial education in the academic year 2015–16 and thus able to predict the odds from learners in the three courses.

Remedial education

Several studies have compared the mean grades of underprepared freshmen with that of prepared college students, or of underprepared students who enrolled in remedial coursework with that of underprepared students who did not enrol in any remedial coursework (Bickley, Davis, & Anderson, 2001; Kolajo, 2004; Worley, 2003). Moss and Yeaton (2006) used regression discontinuity design to examine the effectiveness of a remedial English course offered by a large, multi-campus community college. They found that remedial efforts significantly improved students' academic achievement in the English language. Several reports have indicated that more students require remedial assistance in Maths compared to other subjects (Adelman, 2004; Boylan & Saxon, 1999b; Parsad, Lewis, & Greene, 2003). In another study, Hoyt and Sorensen (1999) demonstrated that a student's high school grades were predictive of the need they would have for remedial education in college or university.

College Students' Adjustment Check List (CSACL)

The CSACL is based on Mooney's Problem Theory (Mooney & Gordon, 1950). In two separate studies, Chu and Tuan (2002) and Tsao (2015) described the CSACL as a good measurement tool for school counsellors and instructors to understand students' problems since it consists of 200 items in the questionnaire. It was found that gender and students in different colleges had a significant difference in scores on the subscales. The CSACL consists of questions related to 10 types of problems: living problem, time management problem, career problem, learning problem, family problem, interpersonal problem, love problem, emotion problem, spirit problem, and physical problem. The rank of 100 percentages is called the PR value. If the PR value is smaller than 84, the participant belongs to normal area. If the PR value is between 85 and 94, it shows the students might have minor trouble in potential and low-risk in learning. If the PR value is higher than 95, it means the students might have major trouble in potential and high-risk in learning. About the major trouble learners, we call them the high-risk group. The list is always drawn before the mid-term exam on the first entry in the first year. The definition of learning trouble means the degree of difficulty in learning method or the pressure of a course was higher than other students. Such students were grouped into poor academic learners. The CSACL alarms and can let tutors and teachers know that these poor learners need more attention.

Multi-Intelligence (MI)

The evaluation of learning performance exists in multiple ways. Gardner and Moran (2006) consider the "MI Theory" to be the most effective because it involves several measures that do not employ pencil and paper. In addition to the logistic concept, there are different bits of intelligence to be discussed on the attribute of courses. If the attribute of two courses is alike in intelligence, then we can arrange the remedial class to support these courses together to save on the limited educational resources. Gardner (1983) originally developed seven specific criteria drawn from many of the biological and psychological sciences that led him to the multi-faceted understanding of intelligence. The bits of intelligence described are Linguistic Intelligence, Logical/Mathematical Intelligence, Musical Intelligence, Visual/Spatial Intelligence, Bodily-kinaesthetic Intelligence, Intrapersonal Intelligence, and Interpersonal Intelligence. Gardner (1999) added Naturalist Intelligence and Existential Intelligence to the above list. With the understanding that intelligence is multifaceted, educators have found that the different types of intelligence are interrelated, and they do not work individually but in concert. In fact, when one intelligence area is used and strengthened, other intelligence may become activated (Armstrong, 2000).

Method

In the present study, we collected and analysed data from four sources: (1) CSACL data (Student's Affairs Office); (2) remedial education data (Academic Affairs Office); (3) performance scores, and (4) student's background information (Computer Centre) as shown in Figure 1. First, we made efforts to find out that out of five colleges (Management, Science & Engineering, Design, Humanities and Social Sciences, and Informatics) in the case University which college has the most high-risk freshmen by analysing the CSACL data.

Second, we explored the remedial education provided by the Office of the Academic Affairs. Third, we analysed final grades obtained in three core courses (BasicMath, Calculus, and Computing) and the learners' background (by Computer Centre of the University). Finally, in the Institutional Research Office, the entire data were analysed in fundamental descriptive statistics and inferential statistics including t-test, ANOVA, *post hoc* test, correlation, and regression analyses to construct predicting models of odds in the core courses.

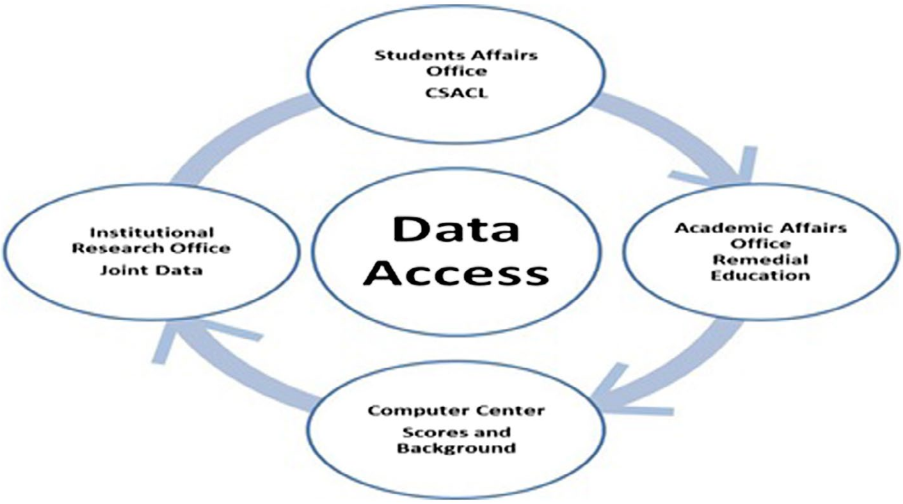

Figure 1. Sources of data for the present study.

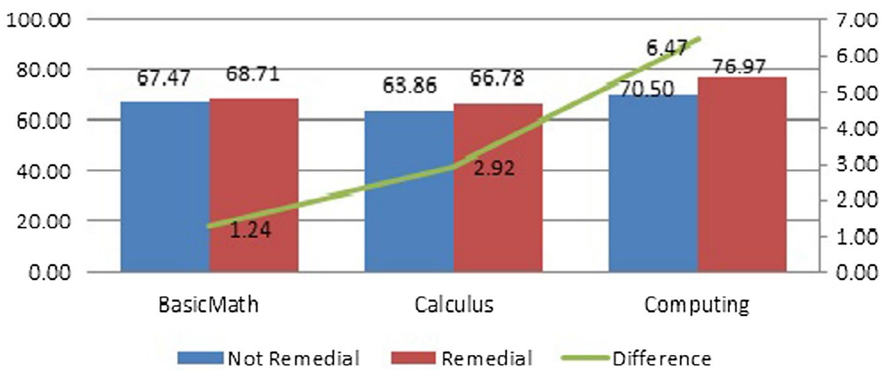

Figure 2. Average grades of three core courses comparative charts.

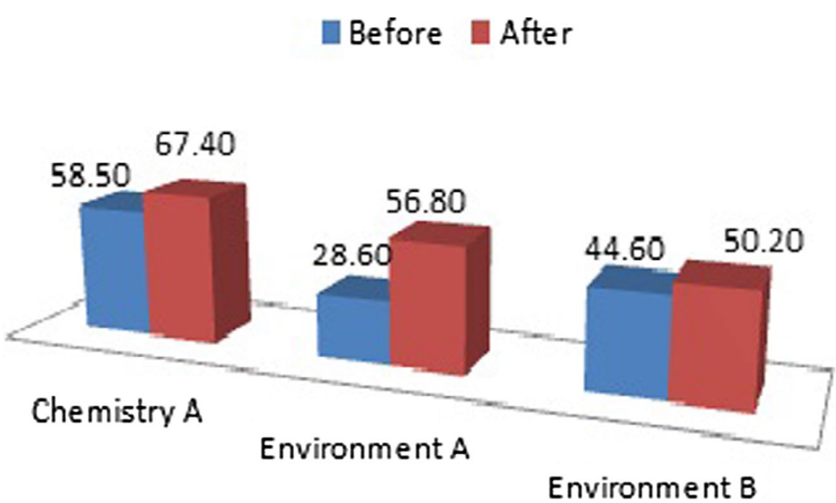

Figure 3. Before/after remedial scores in BasicMath.

Figure 4. Before/after remedial scores in Calculus.

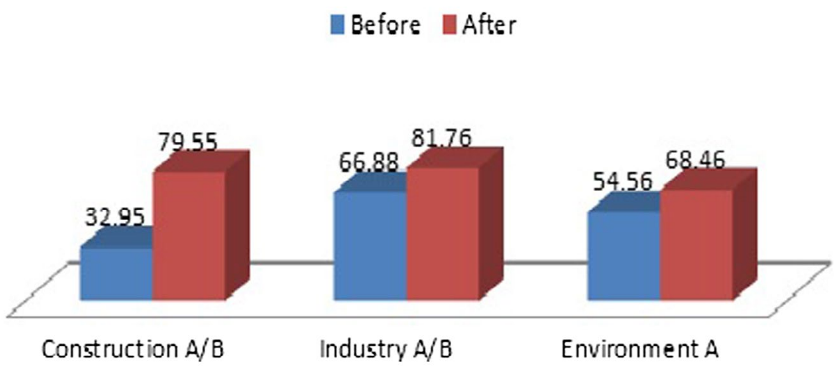

Figure 5. Before/after remedial scores in Computing.

CSACL

The CSACL scale oversaw all freshmen (2,658 participants) from five colleges (Management, Science & Engineering, Design, Humanities and Social Sciences, and Informatics) in the first semester in 2015 in the case University of Technology. Once these learners had been detected by the CASCL, the Offices of Academic and Students' Affairs took the necessary steps in the counselling of these learners. The perplexing frequencies and rates are shown in Table 1. There are four items higher than 15%. In the College of Science & Engineering, the perplexing frequency in the case of learning was 76, and the total number of participants from this college was 394. Therefore, the bothering rate equals 19% (76 x 100/394), showing the highest percentage for the learning problem. Thus, we can conclude that the College of Science & Engineering (S&E) should be our first priority for analysis of remedial education.

In the College of S&E, the participants had more learning and career problems than the other four colleges. Also, in the *post hoc* analyses, it was found that the living problem ranked first in the College of S&E. However, since the focus of this study is on remedial education, we have considered "learning" as the main issue in the next stage.

Variables design

In the College of S&E, in the first year, there are three collective core courses: BasicMath, Calculus, and Computing. In the first semester, these three core courses are compulsory for all freshmen in the four departments (Constructing Engineering, Industrial Engineering and Management, Applied Chemistry,

Table 1. Perplexing frequencies and Post Hoc test in five colleges.

	College					
	Humanities and Social Sciences	Science and Engineering	Design	Informatics	Management	
	(n=478)	(n=394)	(n=400)	(n=388)	(n=998)	
Problem	Frequencies					Post Hoc Test
Living	59	57	79 (20%)	26	118	Design > Informatics
Time management	46	45	69 (17%)	35	85	Design > Informatics
Career	44	63 (16%)	34	57	129	Science and Engineering >Design
Learning	67	76 (19%)	57	44	146	Science and Engineering > Informatics
Family	52	54	25	41	88	
Interpersonal	42	44	49	33	81	
Love	62	47	47	54	110	
Emotion	37	40	34	27	66	
Spirit	40	44	54	24	75	Design > Informatics
Physical	53	39	60	33	96	Design > Informatics

Note: We compare 10 kinds of problems with their perplexing frequencies in five colleges. The dependent variable is the perplexing frequency

and Environmental Engineering and Management). Therefore, the difference between remedial and normal students could be evaluated. In addition to descriptive statistics, we examined three sets of a questionnaire for inferential statistics. For example, what is the relative importance of: (1) gender, (2) high school academic variables (enrolment channel, graduation background, maths scores in enrolment exams), (3) college-related variables (teacher, class, high risk degree, before and after scores of remedial education) in predicting average scores among the three core courses in the first year? Since the classes are different, we transformed the scores from the original ones to Z scores. Then in order to avoid the negative scores, these were transformed into T scores ($T = 10*Z + 50 = 10[(X - M)/SD] + 50$).

Results

In this study, based on the CSACL data, we focused on the freshmen in the S&E College who enrolled in the three core courses (BasicMath, Calculus, and Computing) in the first year and explored the effect of remedial education in the academic year 2015–16.

Comparison between remedial and non-remedial (normal) groups

For the "BasicMath" course, out of 487 students, 106 enrolled in the remedial class. The odds rate of 90% was higher than the total learners (85%) (Table 2). Besides, 30 students classified as high-risk in remedial courses performed relatively better (90%) than those who did not enrol in the remedial education (85%). Similar was the case in "Computing", where 88% odds rate with remedial was higher than 77% of the total number of students. The percentage of high-risk with remedial (76%) was higher than the non-remedial group (70%). In the case of "Calculus", out of 553 freshmen, 279 enrolled in the remedial class and the odds rate was (86%) similar to the total learners. However, the high-risk with remedial got a higher odds rate (84%) than the non-remedial group (80%). Thus, these results indicate that the remedial education was effective since all the scores with remedial education were better than the non-remedial groups. In "Computing" it even attained 6.5 points high (Figure 2).

Table 2. Three core courses odds rate.

Course	Item	Total	Remedial	High risk	
				Without remedial	With remedial
BasicMath	Number	487*	106	20	30
	Odds rate (%)	85	90	85	90
Calculus	Number	553*	279	26	48
	Odds rate (%)	86	86	80	84
Computing	Number	524*	146	20	37
	Odds rate (%)	77	88	70	76

Note: *Total number included freshmen and some senior students. We compare odds rate with each other. Odds rate means passing the evaluation of courses. The dependent variable is odds rate of three courses.

On comparison of scores before and after remedial education among the three core courses, it was observed that scores in all the courses improved after remedial education. We examined the improvement among three classes in BasicMath, four classes in Calculus and three classes in Computing as shown in Figures 3, 4, and 5. The results of the paired t-test among the same samples in the same class indicated a significant difference and contributed to final enhancement in average scores. (Note: See Supplemental data for Table A in the supplementary file.)

In order to detect the characteristics of learners who enrolled in three core courses, we attempted to find their relationship. Only 27 learners in the department of environmental engineering and management enrolled in three courses of remedial education at the same time. By correlation analysis, the result showed that the correlation coefficient of final grades in BasicMath was significant and positive (0.68 high) with Calculus. The common point between BasicMath and Calculus was related to Logical/Mathematical Intelligence. But the attribute of Computing was insignificant and had little relation to the other two courses and had no relation with Logical/Mathematical Intelligence directly. Therefore, remedial support for BasicMath and Calculus can be provided by one teacher thus there can be a saving on the cost of the human resource.

In the next stage, we tried to predict the odds from remedial participants in the college of S&E. In the Taiwan university system, there are several enrolment channels for high school students. Before graduation, students need to take an enrolment exam including Chinese, English, mathematics, and professional courses. In the present study, we only had access to high school maths scores in the three channels: application, recommendation, and joint distribution. First, the channel of application means high school students apply according to their entrance exam scores. Second, the channel of recommendation means high school teachers recommend those students who fulfil the requirement of university education and then students need to get their documents verified and face an interview with instructors in the university. Third, the channel of joint distribution means vocational high school students had to join the admission exams and then get distributed according to their rankings and choices. Therefore, inferential statistics were evaluated only from these three channels. The participants (n=633) included were freshmen and some second-learners in the three courses. However, it is still worth discussing these because the importance indicates that the combined percentage of these three groups was higher than the rest and attained as high as 93%. The participants who enrolled in the remedial education from the three channels could choose either BasicMath only, or BasicMath and Calculus, or BasicMath, Calculus, and Computing at the same time.

Prediction of remedial odds

Later we executed descriptive and inferential statistical analyses including ANOVA, *post hoc* test, correlation and regression analyses, and so on, among three core courses.

Table 3. Frequencies and Post Hoc test in BasicMath.

Factor	Code	Frequency	Percent	Cumulative Percent	Post Hoc Test
Teacher	Teacher1	46	44.2	44.2	
	Teacher2	58	55.8	100	
Class	Chemistry A	46	44.2	44.2	Environment B >Chem-
	Environment A	28	26.9	71.2	istry AEnvironment B >
	Environment B	30	28.8	100	Environment A
Gender	Female	29	27.9	27.9	
	Male	75	72.1	100	
Channel	Application	14	13.5	13.5	
	Recommendation	67	64.4	77.9	
	Joint distribution	23	22.1	100	
High risk	Low	82	78.8	78.8	
	High	22	21.2	100	
Remedial courses	BasicMath	1	1	1	
	BasicMath & Calculus (Computing)	76	73.1	74	
	BasicMath, Calculus, and Computing	27	26	100	
Graduation Background	Not related	50	48.1	48.1	
	Related	54	51.9	100	

Note: We count frequencies of seven variables including Teacher, Class, Gender, Channel, High risk, Remedial courses, and Graduation Background from the access in this study. The dependent variable is the average scores in BasicMath.

BasicMath

There was a total of 104 participants with Maths scores in high school who enrolled in the BasicMath course. The frequencies and percentages of seven independent variables are shown in Table 3. Two teachers were taken as one of the seven variables. Teacher1 was from the Department of Chemistry and Teacher2 from the Department of Environmental Engineering and Management. The other variables included were "gender" (Male or Female), Channel (Application, Recommendation, or Joint distribution), risk level (high or low), remedial courses (BasicMath, BasicMath plus any other course, or BasicMath, Calculus and Computing), and previous background not related or related to the course). Some students in the Department of Industrial Engineering and Management, for example, came from the business subjects in high school. Therefore, the core course in the BasicMath was not directly related to it. According to *post hoc* test, scores in classes show a significant difference. The class of Environment B performed better than the class of Environment A and Chemistry A.

Inferential statistics

In ANOVA, variables of the channel and remedial numbers of courses indicate significant difference (p-vale<.05). The correlation coefficients of variables such as before remedial (t before), after remedial (t after), high school maths (t hm) and average scores (tM) show a significant difference and are interrelated. The higher the scores in before/after remedial and high school maths, the higher were the average grades in BasicMath. (Note: See Supplemental data for Table B & Table C in the supplementary file.)

In regression analyses, the dependent variables were influenced not only by quantitative variables (before/after remedial scores, high school maths scores, etc.) but also by qualitative variables (gender, teacher, class, channel, etc.). Therefore, we incorporated dummy variables in the regression model. The coding of dummy variables is listed as below.

(1) Gender (coded 0=female and 1=male). (2) Teacher(X_1); (0) = Teacher1; (1) = Teacher2. (3) Class(X_2, X_3); (0.0)=Chemistry A; (0.1) = Environment A; (1.0) = Environment B. (4) Channel(X_4, X_5); (0.0)=Application; (0.1)=Recommendation; (1.0)=Joint distribution. (5) High risk (coded 0=low and 1 = high). (6) Graduation background (coded 0=not related and 1=related).

Table 4. Regression analysis in BasicMath.

Variables	β	SE	t	p
Constant	13.309	3.017	4.411	.000**
t after	.445	.078	5.702	.000**
t before	.308	.078	3.961	.000**
X_4	5.072	1.310	3.873	.000**

Note: **.p < 0.01; Adjusted R^2=.645; Estimated standard error=5.440. We did regression analysis from three courses to predict learners' performance from different factors. The independent variables are t before/ t after (before/after remedial scores), and X_4(Channel: Joint distribution). The dependent variable is the average scores in BasicMath.

Table 5. Frequencies statistics in Calculus.

Factor	Code	Frequency	Percent	Cumulative Percent
Teacher	Teacher3	47	19	19
	Teacher4	53	21.4	40.3
	Teacher5	100	40.3	80.6
	Teacher6	48	19.4	100
Class	Construction A	47	19	19
	Construction B	53	21.4	40.3
	Chemistry A	48	19.4	59.7
	Environment A	50	20.2	79.8
	Environment B	50	20.2	100
Gender	Female	69	27.8	27.8
	Male	179	72.2	100
Channel	Application	39	15.7	15.7
	Recommendation	131	52.8	68.5
	Joint distribution	78	31.5	100
High risk	Low	204	82.3	82.3
	High	44	17.7	100
Remedial subject	Calculus	66	26.6	26.6
	Calculus&BasicMath(Computing)	155	62.5	89.1
	BasicMath, Calculus, and Computing	27	10.9	100
Graduation Background	Not related	89	35.9	35.9
	Related	159	64.1	100

Note: We count frequencies of seven variables including Teacher, Class, Gender, Channel, High risk, Remedial courses and Graduation Background from the access in this study. The dependent variable is the average scores in Calculus.

In order to predict the average scores of BasicMath, we coded the learning outcome Y as the dependent variable in the regression model.

The power of explanation of adjusted R^2=0.645 is near R^2=0.67 (Large) and Estimated standard error equals 5.440. Durbin-Watson test < 2, so the sample is independent. And VIF < 5 means the variables are not collinear.

We carried out stepwise regression analyses. The results in Table 4 show variables of before/after remedial scores and the joint distribution of channel were significant. The predictor model of odds in BasicMath is shown as below.

$$Y = 13.309 + .308 * t\text{ before} + .445 * t\text{ after} + 5.072 * X_4$$

If t before $= 60$, t after $= 60$ and $X_4 = 1$, then Y will be 63.56.

The higher the scores before and after remedial courses in the channel of joint distribution, the higher may be the average scores in BasicMath.

Calculus

There were 248 learners with math exam scores who enrolled in Calculus. The frequencies and percentages of seven independent variables are shown in Table 5. There were four teachers for five classes. One of the teachers supported two classes at the same time.

Table 6. Regression analysis in Calculus.

Variables	β	SE	t	p
Constant	2.891	3.361	.860	.391
t before	.584	.056	10.374	.000**
X_1	−12.738	1.619	−7.867	.000**
X_4	−17.438	1.682	−10.370	.000**
Courses	3.366	.767	4.386	.000**
t hm	.120	.044	2.727	.007*
t after	.118	.050	2.384	.018*

Note: **.p < 0.01; *. P < 0.05; Adjusted R^2=.563; Estimated standard error=6.557. The independent variables are t before/ t after (before/after remedial scores), t hm (high school math), X_1(Teacher4), X_4(Class: Environment B), and courses (Calculus, Calculus plus any other course, or BasicMath, Calculus and Computing). The dependent variable is the average scores in Calculus.

Inferential statistics

In ANOVA, it was significant in gender (*p*-vale < .05). In terms of score, female students performed better than males in Calculus. The correlation coefficients of variables such as before remedial (t before), after remedial (t after), high school maths (t hm) and average scores (tM) showed a significant difference and were interrelated. The higher the scores of before/after remedial and high school maths, the higher were the average grades of Calculus. (Note: See Supplemental data for Table D & Table E in the supplementary file.)

In regression analyses, we incorporated dummy variables in the regression model. The coding of dummy variables is listed as below.

(1) Teacher (X_1, X_2); (1, 1) = Teacher3; (1, 0) = Teacher4; (0, 1) = Teacher5; (0, 0)=Teacher6. 2.Class=X_3, X_4, X_5; (0, 0, 0)=Chemistry A; (0, 1, 1)=Environment A; (0, 1, 0) = Environment B; (1, 0, 1) = Construction A; (1, 0, 0)=Construction B.

In order to predict the average scores of Calculus, we coded the learning outcome Y as the dependent variable in the regression model.

Adjusted R square is 0.563, and estimated standard error equals 6.557 and the variables are not collinear. Durbin-Watson test < 2 indicates that the sample is independent.

We carried out stepwise regression analyses. The results in Table 6 show variables like teacher, class, number of remedial courses, before/after and high school maths scores are significant. The predictor model of odds in Calculus is shown as below. Since the X_1(teacher) and X_4(class) is negative to the average scores in Calculus, it indicates that different teachers in different classes will lead to a significantly different final outcome.

$$Y = 2.891 + .584 * t\ \text{before} + .118 * \text{t after} + 3.366 * \text{Courses} + .120 * t\ hm - 12.738 * X_1 - 17.438 * X_4$$

The higher scores of before/after remedial education and high school maths, more remedial courses, students could attain the higher grades in Calculus (Y) barring in the class of Environment A or B, taught by Teacher3 or Teacher4. Since BasicMath and Calculus are classified as Logical/Mathematical Intelligence, their attribute was similar. Therefore, these two courses could be combined for the remedial education.

Computing

There were 132 learners with maths exam scores who enrolled in the Computing course. The frequencies and percentages of seven independent variables are shown in Table 7. There were three teachers for five classes. Two teachers supported two classes at the same time.

Table 7. Frequencies and Post Hoc test in Computing.

Factor	Code	Frequency	Percent	Cumulative Percent	Post Hoc Test
Teacher	Teacher7	18	13.6	13.6	
	Teacher8	66	50	63.6	Teacher7>Teacher8
	Teacher9	48	36.4	100	Teacher7>Teacher9
Class	Construction A	45	34.1	34.1	Industry A,B> Construction A
	Construction B	21	15.9	50	Industry A,B >Construction B
	Environment A	48	36.4	86.4	Industry A,B > Environment A
	Industry A	8	6.1	92.4	
	Industry B	10	7.6	100	
Gender	female	38	28.8	28.8	
	male	94	71.2	100	
Channel	Application	11	8.3	8.3	
	Recommendation	80	60.6	68.9	
	Joint distribution	41	31.1	100	
High risk	Low	108	81.8	81.8	
	High	24	18.2	100	
Remedial subject	Computing	21	8.3	8.3	Computing> Computing&Basic-Math(Calculus)Computing> Basic-Math, Calculus and Computing
	Computing & BasicMath(Calculus)	84	60.6	68.9	
	BasicMath, Calculus, and Computing	27	31.1	100	
Graduation Background	Not related	50	37.9	37.9	
	Related	82	62.1	100	

Note: We count frequencies of seven variables including Teacher, Class, Gender, Channel, High risk, Remedial courses and Graduation Background from the access in this study. The dependent variable is the average scores in Computing.

Inferential statistics

In order to carry out cross-analyses, we divided average grades of Computing into three levels: high, middle, and low. It was found that variables of teacher, class, and the channel had significant differences ($p < .05$ by chi-square test). Teacher7 in the department of Industrial Engineering and Management showed higher scores in Computing. The enrolment channel of recommendation was the best in Computing.

The results of *post hoc* test showed that variables like teacher, class, and number of remedial courses were significant. Students who enrolled in Computing need not enrol in BasicMath and Calculus for remedial education since the attribute of Computing is different from maths. The Computing course extends not only the Logistic Intelligence but also Spatial and Design Intelligence in Word, Excel, and PowerPoint.

In ANOVA, graduation background was related to Computing, especially for the participants who graduated in the subject of Information in high school. Those whose major was Information could understand the Computing course easily and quickly.

The correlation coefficients of variables such as before remedial (t before), after remedial (t after), and average scores (tM) showed a significant difference and were interrelated. The higher the scores of before/after remedial education, the higher were the average grades in Computing. But scores in high school maths were neither significant nor related to Computing. The attribute of Computing was marginally related to the other two courses but had no direct relationship with Logical /Mathematical Intelligence. (Note: Please refer to Supplemental data for Table F & Table G in the supplementary file.)

In regression analyses, dummy variables were incorporated in the regression model. The coding of variables is listed as below.

(1) Teacher(X_1, X_2); (0, 0) = Teacher7; (0, 1)=Teacher8; (1, 0)=Teacher9. 2. Class=X_3, X_4, X_5; (0, 0, 0)=Construction B; (0, 0, 1)=Construction A; (0, 1, 1)=Industry A; (0, 1, 0) = Industry B; (1, 0, 1)=Environment A. 3. Channel: (X_6, X_7); (0.0) = Application; (0.1)=Recommendation; (1.0)=Joint distribution.

Table 8. Regression analysis in Computing.

Variables	β	SE	t	p
Constant	37.379	3.821	9.783	.000**
X_4	19.980	2.189	9.125	.000**
t after	.185	.074	2.510	.013*
X_7	3.293	1.537	2.142	.034*

Note: **.p < 0.01; *. P < 0.05; Adjusted R2=.409; Estimated standard error=8.623. The independent variables are t after (after remedial scores), X4(Class: Industry B), and X7(Channel: Recommendation). The dependent variable is the average scores in Computing.

In order to predict the average scores of Computing, we coded the learning outcome Y as the dependent variable in the regression model.

Adjusted R square is 0.409 and estimated standard error equals 8.623. Durbin-Watson test < 2 explained that the sample was independent. VIF < 5 means that the variables were not collinear.

We carried out stepwise regression analyses. The results in Table 8 show that variables like class, after remedial scores and enrolment channel were significant. The predictor model of odds in Computing is shown as below.

$$Y = 37.379 + 19.980 * X_4 + .185 * t\text{ after} + 3.293 * X_7$$

If the participant can get higher remedial scores from the enrolment channel of recommendation and study in the Department of Industrial Engineering and Management, he or she would get higher average scores in Computing.

Discussion

In ANOVA, *post hoc*, cross, correlation, and regression analyses, the significant variables included gender, teacher, department, high school performance, enrolment channel, and remedial course loads. The detailed descriptions are discussed below.

Gender

The scores achieved by female students were higher than the male students in Calculus. Attitude towards Maths differed by gender. Males generally had more positive attitude towards maths than females; a similar observation was reported by Ma and Cartwright (2003). According to them, female students generally perceive maths as less useful and exhibit higher maths anxiety, although they typically earn higher grades than do males (Ma & Cartwright, 2003). In the present study, this difference between male and female students was marginal. It was observed that out of total 76 high-risk students, females constituted 20% (23/118) compared to 19% of males (53/276). It seems that female students who had pressure about the nature of mathematics pushed themselves to study diligently to get higher scores.

High school maths, skill, and enrolment channel

From correlation analysis, it was observed that the performance in high school maths had an influence on BasicMath and Calculus. A number of studies have investigated how the quality of high school maths preparation impacts success at college-level mathematics (Adelman, 1999; Boaler, 1997; Choy, Henke, Alt, Mendrich, & Bobbitt, 1993; Dillworth, 1990; Henke, Choy, Geis, & Broughman, 1996; Horn, Hafner, & Owings, 1992). Lee, Burkam, Chow-Hoy, Smerdon, and Geverdt (1998) claimed that specific types of high school maths courses are strongly associated with college mathematics performance (e.g., academic maths courses). In another study, Trusty (2002), Trusty and Niles (2003) reported that high school academic preparation had a strong association with college maths performance in bachelor's degree programmes. A multiple regression analysis showed that SAT-Math scores marginally contributed to students' performance in college-level mathematics (Atuahene & Russell, 2016). Therefore, it would be prudent to advise the underprepared students (who had low scores in high school maths) to enrol in remedial education at the entry level in the first year itself.

Stage and Kloosterman (1995) observed that students' prior experiences and skills, the highest level of mathematics completed, and mathematics skill level after completing high school were posited to be related to students' beliefs about mathematics and about themselves in relation to mathematics.

In our study, about high school experience, there are two types of enrolment channels to be discussed. First, the higher the scores after remedial from the recommendation channel, and in the Industrial Engineering and Management department, the higher were the average scores in Computing. The group in "Superior Skill" or "Recommendation" channels performed well in professional courses. Computing includes Spatial and Design Intelligence. Therefore, the background in "Information" in high school helped to get higher scores in Computing. Second, it could be predicted that the higher the scores before/after remedial courses in the channel of "Joint distribution", the higher will be the average scores in BasicMath. Learners from the "Joint distribution" achieved higher scores through repeated practice in remedial education.

Teacher and department

In our study, it was noted that the average scores of students were related to teachers in different classes and different departments. For example, in the case of "Computing" students in the class of Teacher7 in the department of Industrial Engineering and Management achieved higher scores. Akin to our study, Stage and Kloosterman (1995) described the influence of teacher characteristics on the performance of students in mathematics.

According to Khouyibaba (2015) a good remedial maths teacher must have the following attributes: (1) A passion and motivation for the profession, (2) Competency and professionalism, (3) The ability to give individual attention and be available to the students, and (4) The ability to establish high standards in the classroom.

Multi-intelligence and course load

Logical/Mathematical Intelligence is related to maths courses. Those who enrolled in remedial courses in BasicMath and Calculus achieved higher scores. Visual/Spatial Intelligence is closely related to skill training and prior high school experience. The ability of Computing is associated with office Word, Excel, and PowerPoint which were taught in the subjects of Information in high school. The spatial intelligent student succeeds in areas like art, design, and imaging (Armstrong, 2000). With the understanding that intelligence is multifaceted, educators have found that the different types of intelligence are interrelated, and they do not work individually but in concert. In fact, when one intelligence area is used and strengthened, other intelligence become activated (Armstrong, 2000). About the number of remedial courses, Martin (2003) indicated tutor treatment and a reduced course load lead to success by low achievers. If a high-risk learner participates only in one remedial course (Computing or related math courses) at a time, the chances of success are more due to low learning load.

Limitations

In Taiwan, there are several university enrolment channels for high school students. Before graduation, students are required to take an enrolment exam including Chinese, English, mathematics, and professional courses. In this study, our university had access only to scores in enrolment exams from the channels of application, recommendation, and joint distribution.

When random assignment may not be of practical use, the regression-discontinuity design (RDD) is a very useful statistical technique to make inferences (Lesik, 2006). In this study, we have done the analysis using the data from institutional research database and not by the first-hand data from an experiment. For example, Bettinger and Long (2009) estimated the effects of remediation and the Local

Average Treatment Effect in an ad hoc regression model. We want to analyze not only the unprepared group but also the ready learners who study BasicMath, Calculus, and Computing in the College of Science and Engineering. Therefore, it is more convenient for us to apply ad hoc regression rather than RDD. In the future, we can focus on small samples to apply RDD to compare the difference between the treatment and control groups.

Implication for further research

Two areas for further research can be indicated: (1) To explore which core courses will be affected by Mandarin or English ability with the scores from different enrolment channels after high school. (2) To find the effect of multi-intelligence theory, if the remedial education could be separated into multiple evaluation methods, such as e-learning, teamwork, and peer support, among others.

Conclusions

The present study demonstrates that CSACL data available with the Offices of Students' Affairs can help the authorities to identify potential high-risk freshmen in the university. Also, it demonstrates that to alleviate the problem of unpreparedness and to check failure and dropout rates, an effective remedial system could be developed by the combined efforts of the Office of Students' Affairs, Computer Centre, Academic Affairs, and the Institutional Research. Our study supports findings of other researchers that gender, teacher, department, high school performance, enrolment channel, and load of the remedial course influence learning outcomes. With the limited budget for tutorial resources, it is important to decrease the cost in terms of an attribute of courses. Since BasicMath and Calculus belong to Logical/ Mathematical Intelligence, the same teacher can be assigned to teach these subjects to save on the cost of human resources. Finally, use of multi-evaluation approaches in different enrolment channels can attain higher retention. The group in Superior Skill or Recommendation channels perform better in professional courses, while learners from Joint distribution channels often achieve higher grades with repeated practice and pass the exam smoothly.

Disclosure statement

No potential conflict of interest was reported by the authors.

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