A Preliminary Study on Prediction Models for English Web-based Remedial Education: Application of Data Mining Theory

RONG ZHANG
Nishinippon Institute of Technology
Graduate School of Information, Production and System
Waseda University
JAPAN
zhang@nishitech.ac.jp

YUE ZHOU
Graduate School of Information, Production and System
Waseda University
JAPAN
zhou-yue@fuji.waseda.jp

FUKUYA ISHINO
Waseda University
JAPAN
ishino@waseda.jp

Abstract: - Remedial course is a product of a well-developed higher education system. As universities/colleges become more available to high school graduates, competitiveness in the entrance exam is lessened and demand for students' basic scholastic abilities diminishes in admission. This social phenomenon causes two problems for the implementation of higher education: (1) Students can't comprehend lectures due to their lack of basic academic knowledge; (2) The unbalanced distribution of students' scholastic achievements is believed to be the most significant factor weakening teaching effectiveness. Many universities/colleges, especially those in developed countries and areas, have to integrate remedial courses into their first-year education in order to help the students compensate for what they should have mastered in the previous learning. This study reports an English remedial course carried out for all freshmen in Nishinippon Institute of Technology, Japan, and focuses on the regression analysis for determinants of students' score changes. Two prediction models are postulated, so that the issue is being examined from different perspectives. In the first model, students' total engagement in learning, intercultural communication competences and computer operation skills are proved to be responsible for their score changes. In the second model, students' positive attitudes towards remedial course and web-based learning turn out to be a crucial factor to promote their performances.

Key-Words: - Remedial courses, Multiple regression analysis, Prediction model, English education, Web-based learning

1 Introduction

Remedial education has become an indispensable component of higher education in certain countries/areas [6] [11] [13] [21]. According to the National Center for Education Statistics in USA, 72.8% of American degree-granting institutions offered remedial services through 2006-2007 [15]. As Hoyt proved, remedial education functions as a significant factor closely related to student attrition rates in community colleges of America [8]. In Japan, government attention has been given to the issue of remedial education in recent years. Owing to the considerate decrease in the population of younger generation, Japanese universities/colleges have to accept "addition of students who need support in the general education classroom" [14], and frameworks for remedial education were established by central government MEXT to provide follow-up supports to these students with learning disabilities [6] [11].

The objective of remedial education is to reinforce the quality of practice in postsecondary developmental education and provide students with more chances to realize potential successes in academic learning [12] and diminish the gap between the top level students and the bottom. Lack of basic knowledge in common subjects prevents them from perfect comprehending lectures on his/her major [20]. And the unbalanced distribution of students' academic proficiencies distresses both the teacher and students [6].

Because the remedial course often parallels the normal curriculum study for graduation in Japanese universities/colleges, web-based learning is often employed as an effective tool to lessen the burden of teachers. Extensive researches have been conducted to demonstrate the effectiveness of e-based learning [3] [6] [17] [22] [23], but few have ever attempted to examine remedial course from a comprehensive perspective and investigate what on earth contributes to the improvement of students' academic performances in an e-learning environment. The same school resources can "produce many educational outputs" [7] [10]. And web-based learning is such a complex process of teaching/learning that both technological devices and environmental factors are involved [21]. Therefore, it is crucial to figure out those complex non-causal relationships potentially existing among those factors which lead to the various education productions.

This paper establishes the study about English remedial education for Japanese learners on the assumption that individual commitment to academic learning activities, intercultural communication and computer operation skills are closely related to the outcome of English remedial education course through a web-based learning tool [9] [16]. They serve as determinant variables in the optimized model for predicting the outcome of remedial education and the fitness of the equation postulated through multiple regression analysis is also examined.

2 Algorithm of Analysis

The theory which lays the ground for this study is the linear regression analysis method proposed by Karl Pearson. The outcome of English remedial education (W), which reflects students' score changes after the course study, functions as the dependent variable, with factors of related aspects as the independent variables (Y). We suppose a quasi-linear relationship exists in this framework and the predictive regression model should follow the typical monomial equation:

$$\begin{aligned}\hat{W}_i &= f\ (Y)\\ &= ß_0 + ß_1 Y_1 + \beta_2 Y_2 + \ldots + \beta_i Y_i + \varepsilon_i\end{aligned}$$
$$(\, i = 1, n) \qquad (1)$$

Dependent variable W_i indicates score change of the *i*th sample student after remedial education course study and Y_i refers to the *i*th independent variable which correlates maximally with W_i. β_i works as the determinant coefficient of the *i*th independent variable and is figured out through the method of least squares. Residual ε_i is an observational error between the expected score change and the observed score change and $ß_0$ is the intercept of the straight line. Since our purpose in our current study is to postulate an equation for preliminary prognosis, we ignore the residual ε_i temporarily and leave the research of this exponent to future work.

As mentioned above, there are noticeable researches on how to improve the effectiveness of English remedial education in Japan. But most of them inspect the issue from a single scope with limitation of persuasiveness. As far as we are concerned, there is seldom any practical study on the prediction of the outcome of English remedial education from a synthesized perspective. Education production outcome (Y) does not depend on students' academic attainments only [1] [5]. Students' cognitive beliefs and non-pedagogical relevant factors also exert critical impacts on the output of their learning activities [16] [19]. In the case of English remedial education, independent variables (Y) consist of a combination of certain factors, including students' total academic commitments (H), correct understanding about intercultural communication (J) and desirable proficiency in computer operation skills (L). Academic relevant information includes students' total motivation, attitudes and commitments towards all learning activities. In summary, the post-course score change (W) in English remedial education is caused by a sophisticated process which holds the following three vectors in its synergetic action: total academic commitment (H), correct understanding about intercultural communication (J) and admirable computer operation skills (L):

$$\begin{aligned}\hat{W} &= f\ (Y)\\ &= f\ (H, J, L)\end{aligned}$$

$$= f\ (H)\ +\ f\ (J) + f\ (L) \qquad (2)$$

We assume that the three vectors all have a positive impact on students' test score changes. The reinforcement of any vector results in some increase in students' learning proficiencies.

3 Scenarior

3.1 Data

We collected 121 effective samples in 2007 from the freshmen of Computer Design Faculty in Nishinippon Institute of Technology, Japan. They are required to complete a remedial course study online from May to November, 2007. Both pre-course test and post-course test were held and the same set of questions was used in order to find out the exact changes in students' performances. They were also encouraged to answer three questionnaires, especially about their cognitive thinking about English study, remedial course, computer operation and intercultural communication. We also got the permission to use students' personal digital files as part of our data.

Thus, the data is made up of three inquiries and student management record provided by the university: (1) Total academic performances (student management record): including school attendance rates, average scores of all subjects in the first semester, performances in the web-based self-learning activities (H_1); (2) Inquiries on their motivation, attitudes and commitments towards learning: including their learning strategies, response towards the assessment received from teacher, their anxiety degrees about credits for graduation, et al. (H_2); (3) Inquiries on their understanding about intercultural communication and their involvement in it (J); (4) Inquiries on computer operation skills and their inclination to employ computer as a tool in their learning (L). Both the first and the second items are considered explanatory variables belonging to the same category (H) in this study. Consequently, the three vectors in equation (2) are adequately reflected in the data collecting process.

3.2 System

Students are supposed to carry out self-study through a web-based learning system called ASP (Active Server Pages) (Fig.1). It is the most typical software being used for pedagogical activities in Japan. The tool aims at an improvement of students' basic knowledge about English (on both grammatical rules and vocabulary) which should have been mastered during their middle school and high school study. The purpose of this course is to help them compensate for their deficiencies in English study as soon as possible so that they can keep up with the standard university/college curriculum education. Students can access the didactic materials and exercises from a specific log-in window wherever the Internet is accessible. Teachers can check their progresses with the study instantaneously. The well-prepared contents and the convenient assessment functions largely facilitate teachers. Its built-in defect is that that revision can be made promptly, since web-managers are fully responsible for the server.

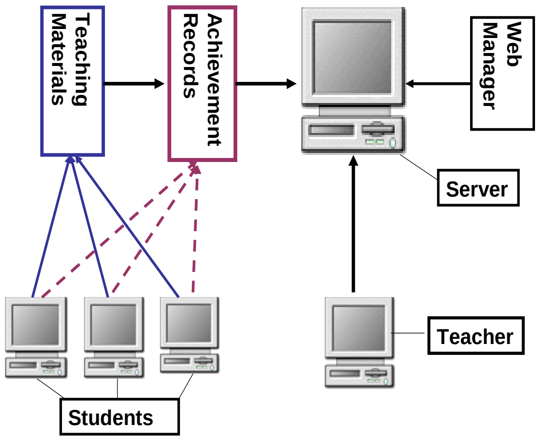


Figure 1: Framework of ASP System

We used very simple and basic questions in the pre-course test and post-course test for the purpose of not frustrating the students, especially low-proficient students at the very beginning of their university/college study. Confidence is supposed to be a factor considerably affecting their attitudes and performances in their study, which are justified in our analysis. Students score in nearly all the ranks, which indicates the extremely unbalanced distribution of their scholastic abilities (Table 1). The score change in the tests is used not only as a figure to represent the outcome of their self-study, but also significant index (dependent variable) to examine the effectiveness of this online remedial course.

3.3 Result

Table 1: Histogram of Pre-course Test Score

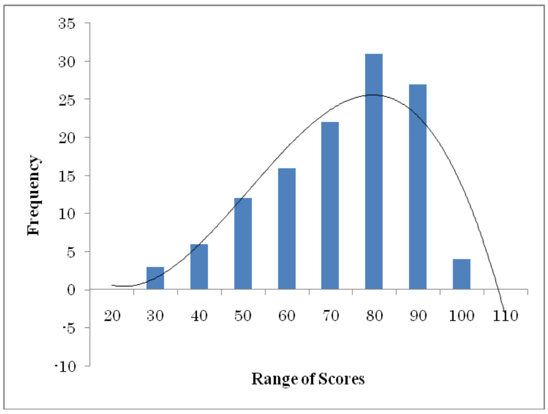


Table 2: Statistics of Observed Score Changes

Average	9.5
standard residual	1.01
standard deviation	11.1
minimum	-28
maximum	36
total	1148
sample	121

Table 3: Histogram of Observed Score Changes

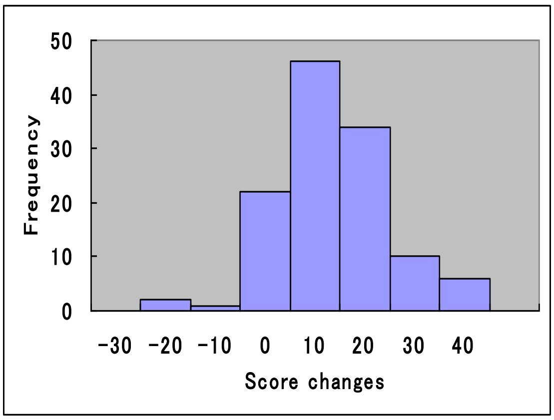
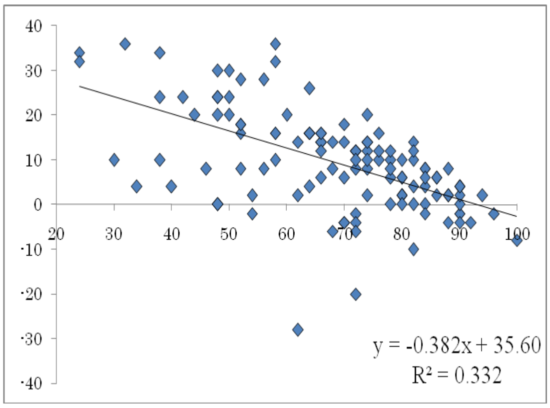


Table 1 implies the distribution of students' pre-course test scores. Table 2 suggests the average score change in the post-course. An improvement in test score (9.5 points) is observed, which stands for a certain progress in students' English proficiencies. The result once more justifies the outcome of many previous studies that web-based learning efficient for the improvement of English learners' grammatical proficiencies [17] and some other reading and listening skills [2] [25].

Table 4: Correlation between Post-course Score Changes and Pre-course Test Scores



Although most changes happened within a scope of 0 ~ 20 points (Table 3), the gap between the minimum score change and the maximum score change reaches 64 points. As an inevitable phenomenon, pre-course test score turns out to be the most fundamental determinant in post-course score change -- students whose pre-course test scores are higher tend to show a non-significant change in their post-course test performance (Table 4). This tendency once more strengthens our doubt for this study: what are the other determinants contributing to the score changes except for students' pre-course test scores?

4 Discussion

4.1 Regression Analysis

We conducted multiple regression analysis repeatedly by using excel in order to find out those independent variables which help construct the optimized model for the prediction of post-course score changes. According to the criterion suggested by Ueta [24], multiple regression analysis should be based on the following equation. The parameter with the largest p-value is deleted each time until only one parameter is left:

$$\hat{W}_i = 1-(1-R^2)(n+k+1)/(n-k-1) \qquad (3)$$

R^2 is the determinant coefficient and stands for the contribution ratio. k is the number of independent variables (number of parameters used each time to conduct the analysis). n stands for number of samples which is 121 in this study.

Table 5: Optimized Model (1) for Prediction of Score Changes

Independent Variables	Coefficients
Intercept (I)	-17*
Pre-course test score (T)	-0.483**
Average score of total subjects (A)	0.736**
Encouragement from positive evaluation (M)	2.17**
Credit anxiety (U)	1.21
Existence of foreign friends (F)	2.31**
Curiosity towards foreign cultures (C)	1.56*
Self-confidence in making foreign friends(Q)	1.97**
Easiness in contact with foreign people (G)	2.28**
Appropriate dependence on computer (O)	1.74**
Self-confidence in computer operation (S)	2.19**
Willingness to improve one's computer operation skills (E)	1.11
Adaptiveness to the rapid progress of scientific technology (D)	1.51*

*p<0.05 **p<0.01

Table 5 shows the individual coefficient of each independent variable which helps create the maximum $\hat{W}_i$ (0.525). That means, the equation proposed can interpret 52.5% of the dependent variable $\hat{W}_i$. All of 12 determinant variables demonstrate a positive relationship with the post-course score changes except the specific item ---- pre-course test score. The improvement of any determinant variables leads to an increase in the figure of their post-course test score. Most p-values for the determinant variables are under .01 other than two parameters – "credit anxiety"(U) and "willingness to improve one's computer operation skills"(E). Consequently, we infer the following formula as the optimized model for the prediction of students' score changes ($\hat{W}_i$) after the English remedial course study through web-based learning:

$$\begin{aligned} \hat{W}_i = & -17(I) \\ & + 0.483 * T_i + 0.736 * A_i \\ & + 2.17 * M_i + 1.21 * U_i \\ & + 2.31 * F_i + 1.56 * C_i \\ & + 1.97 * Q_i + 2.28 * G_i \\ & + 1.74 * O_i + 2.19 * S_i \\ & + 1.11 * E_i + 1.51 * D_i \\ & (i = 1, n) \qquad (4) \end{aligned}$$

4.2 Validating the Prediction Model through Correlation

Table 6: Correlation between Expected Score Changes and Observed Score Changes

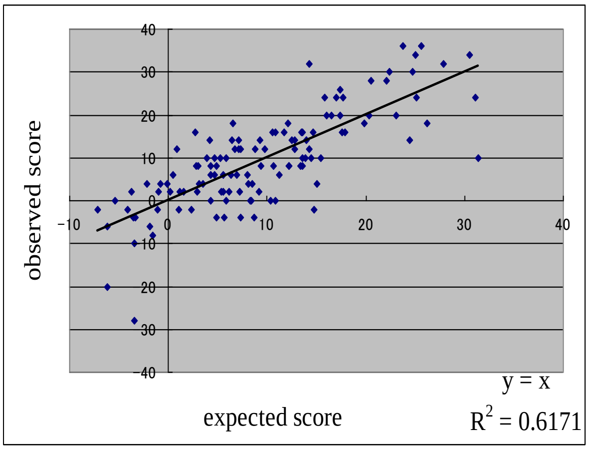
	Expected Score Change	Observed Score Change
Expected Score Change	1	0.786
Observed Score Change	0.786	1

In order to testify the fitness of equation (4), we intended to confirm the correlation between the expected score changes ($\hat{W}$) and the observed score changes of each sample student. According to the compendium method proposed by Ueta, correlation among the factors is believed to exist if the following equation functions [24]:

$$R^2 > 4 / (n+2) \qquad (5)$$

In this study, the sample number (n) is 121. Therefore, we expect R^2 to be more than 0.033 in order to assure the correlation. We figured out the expected score changes $\hat{W}$ for all students and compared them with their respective observed score change. The result suggests that R = 0.786 (Table 6) and R^2 turns out to be 0.617 (Table 7), much higher than the specified value 0.033. Therefore, we can definitely make the conclusion that there is an extremely strong correlation between the observed score changes and the expected score changes calculated by using the optimized model postulated above.

Table 7: Correlation between Observed Score Changes and Expected Score Changes



4.3 Validating the Prediction Model through Visual Approximation Curves

Table 8: Approximate Curves for Observed Score Changes and Expected Score Changes

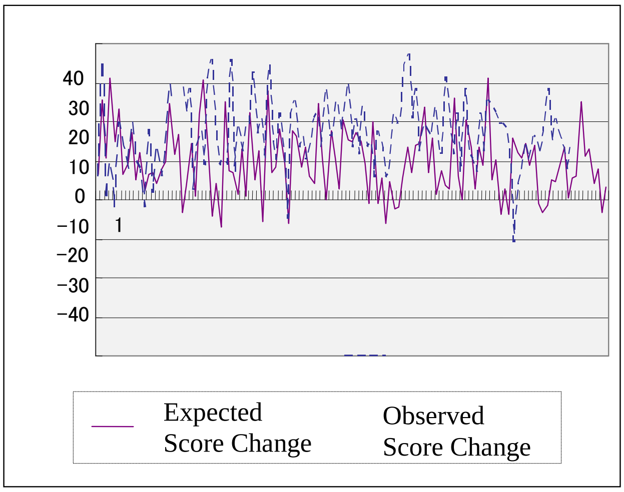
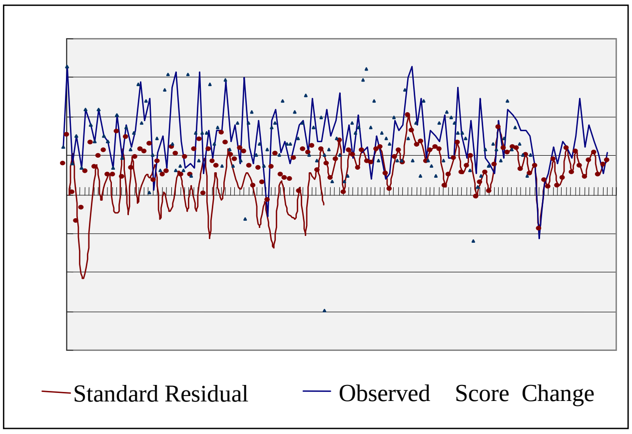


Table 8 describes the observed score change and the expected score change by using approximate curves. Most parts of the polygonal curves ---- the dotted line and the solid line, are crossing over, which further evince the appropriateness of our prediction formula. In sum, our selection of dependent variables for this study is rational and the prediction equation we proposed for post-course score changes is effective. Table 9 demonstrates that standard residual curve appears as a shadow of the curve for observed score changes. The former line is much more closed to the *x* axis than the latter. Needless to say, the index of standard residual is a much smaller figure comparing with the value of observed score change.

Table 9: Approximate Curves for Observed Score Changes and Standard Residuals



4.4 Examination of Impact Degrees

The impact degree (V_i) of each independent variable is another important exponent for the measurement of each factor's impressiveness. It helps clarify the question we hold in mind that what on earth causes the differences in students' score changes. The impact degree (V_i) is calculated according to the following equation:

$$V_i = f(R, B) = R_i * B_i \quad (i = a, m, u, f, c, q, g, o, s, e, d) \qquad (6)$$

R_i is the coefficient for the respective determinant variable listed in Table 4. B_i is the range of each parameter in the original data, by subtracting the minimum value (Z_{ib}) from its maximum (Z_{iy}):

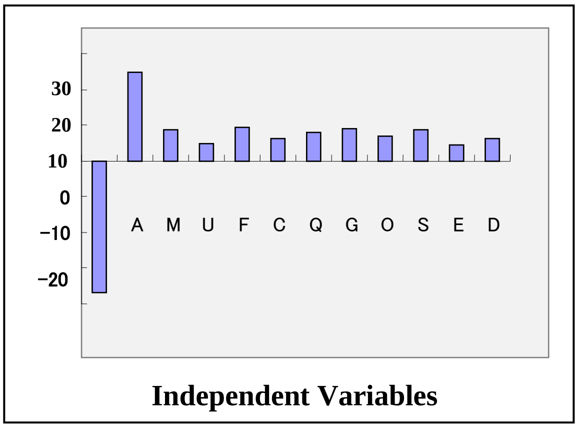
$$B_i = Z_{iy} - Z_{ib} \qquad (7)$$

Thus,

$$V_i = R_i \ * \ (Z_{iy} - Z_{ib}) \quad (i = a, m, u, f, c, q, g, o, s, e, d) \tag{8}$$

Table 10 signifies the impact degrees of all the independent variables included in the optimized model (Equation 4). Except for the item of pre-course test score (T), the average score of total subjects (A) turns out to be another noteworthy determinant, while other independent variables show no remarkable difference in their impacts on the dependent variables.

Table 10: Impact Degrees of Independent Variables



4.5 Auxiliary Analysis

As we manifested in equation (2), the post-course score change in English remedial education (Y) is a combined function of total academic commitment (H), correct understanding and active attitude toward intercultural communication (J) and admirable computer operation skills (L). Likewise, the indexation of determinants H, J and L is also an outcome achieved by the coordination of several independent variables respectively. The synthesized operation of the independent variables in the optimized model can be interpreted as in the following equations:

$$V_h = f\ (A, M, U) \tag{9}$$

$$V_j = f\ (F, C, Q, G) \tag{10}$$

$$V_l = f\ (O, S, F, D) \tag{11}$$

In this study, the noticeable function of the index pre-course test score is to work as a normal for us to make judgment about changes in students' test performance. Therefore, we treat T as a reference rather than a common independent variable and list it as a completely separate independent index. The prerequisite for the classification here is that all the independent variables hold a positive relationship with the dependent variable ($\hat{W}$), except the item pre-course test score (T). Hence, the impact degrees of these three determinants are decided according to the following equation:

$$\begin{aligned} V_h &= f\ (A, M, U) \\ &= f(A) + f(M) + f(U) \\ &= V_a + V_m + V_y \\ &= R_a * (Z_{ay} - Z_{ab}) + R_m * (Z_{my} - Z_{mb}) \\ &\quad + R_m * (Z_{uy} - Z_{ub}) \end{aligned} \tag{12}$$

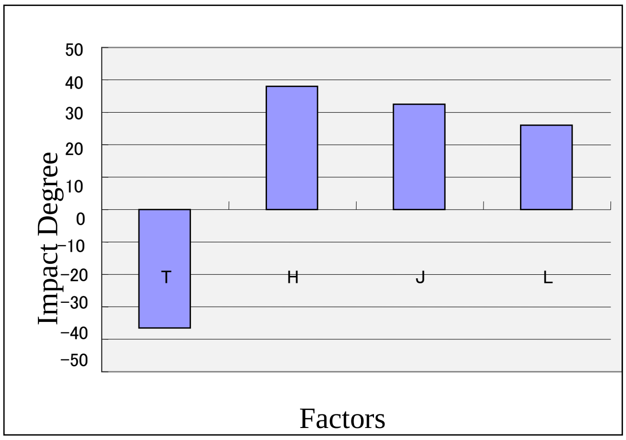
Accordingly,

$$\begin{aligned} V_j &= f\ (F, C, Q, G) \\ &= f(F) + f(C) + f(Q) + f(G) \\ &= V_f + V_c + V_q + V_g \\ &= R_f * (Z_{fy} - Z_{fb}) + R_c * (Z_{cy} - Z_{cb}) \\ &\quad + R_q * (Z_{qy} - Z_{qb}) + R_g * (Z_{gy} - Z_{gb}) \end{aligned} \tag{13}$$

$$\begin{aligned} V_l &= f\ (O, S, F, D) \\ &= f(O) + f(S) + f(F) + f(D) \\ &= V_o + V_s + V_f + V_d \\ &= R_o * (Z_{oy} - Z_{ob}) + R_s * (Z_{sy} - Z_{sb}) \\ &\quad + R_f * (Z_{fy} - Z_{fb}) + R_d * (Z_{dy} - Z_{db}) \end{aligned} \tag{14}$$

Table 11 suggests the impact degrees of different aggregations of determinant factors. H appears to be most substantial in its impact degree with J in the middle and L the slightest. Students' total academic involvement, intercultural communication competences and computor operation skills contributer to their final score changes. The improvement of any of the three factors can increase the scope of their progress in test. Certain, the most meaningful instruction should be centered around the point of how to get them engaged in all learning activites maximumly. This result perfectly agrees with our hypothesis at the scheming stage.

Table 11: Impact degrees of different groups of determinant factors



5 A Supplementary Model

Through the examination above, we can come to the conclusion that the prediction model for students' score changes is not only explicit in interpreting the algorithm of dependent variable, but also abundantly suggestive of pedagogical instructions. But there is one shortcoming with the equation (4): Because of the excessive number of determinant variables, it is not intuitive enough to reflect the original nature of those factors. Although we incorporate them into three aspects, the attributes of the original data may be unconsciously modified or converted during the process. Hopefully, a more concise prediction model can compensate for the deficit of the equation (4).

We decide to figure out those independent variables which hold direct correlation with students' score changes before conduct regression analysis (Table 12). According to equation (5), when R^2 is more than 0.033, correlation is believed to exist among the variables. Thus, we summarize all the factors whose coefficient (r) is above 0.185. Besides the item "pre-course test score", only factor "credit anxiety" from equation (4) appear in the list. Four independent variables among the fourteen variables are proved to be responsible for students' score changes: "pre-course test score" (Y_1), "I can catch up with the teacher in class" (Y_2), "I feel English learning is more enjoyable than before"(Y_3), and "The content is not difficult"(Y_4). Prediction model including these three factors can be organized as the following (Table 13):

$$\hat{W} = f(Y) = 37.9 + (-0.409)* Y_1 + 2.01 * Y_2 + 1.93 * Y_3 + 19.6 * Y_4 \tag{15}$$

Table 12: Correlation of Post-course Score Changes and Other Independent Variables

Independent Variable	Coefficients
Pre-course test score	-0.576
The remedial course is not difficult.	0.275
I find English learning is more enjoyable than before.	0.258
I am doing extra learning in English.	-0.241
There are still many questions unsolved.	0.235
I always review after the class.	0.233
Remedial course is necessary.	0.229
I can catch up with the teacher in class.	0.225
Credit anxiety (I am learning for credits.)	0.222
I always prepare before class.	0.221
I like computer games.	-0.215
I do not want to lose my current English ability.	-0.2
One's English proficiency depends on his/her efforts.	0.2
Computers are more reliable than human beings.	-0.181

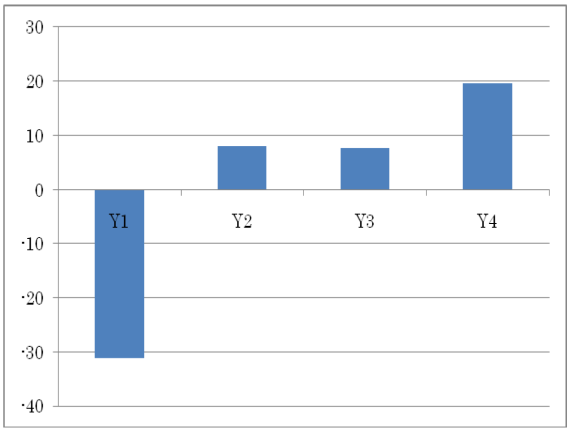
** $p < 0.01$

Although the figure of $\hat{W}_i$ calculated this way is much lower (0.403) than the case of equation (4), the simplified formula is more conveniently achieved and gives a more intelligible description for the question of how students' score changes in tests occur. Table 14 implies the impact degrees of the four determinants calculated by equation (15). It helps explain the dependent variable from psychological perspective ---- Students, who do not have much difficulty in dealing with the contents and are getting more confident in their learning tend to raise their score more efficiently. In order to address this issue clearly, we add the impact degrees of Y_2 and Y_2 to provide a more striking illustration (Table 15). Inevitably, pre-course score plays a negative role in mirroring students' score changes as usual.

Table 13: Optimized Model (2) for Prediction of Score Changes

	Coefficient
Intercept	37.9
Pre-course test score	-0.409**
I can catch up with the teacher in class.	2.01
I find English is more enjoyable than before.	1.93
The remedial course is not difficult.	-19.6**

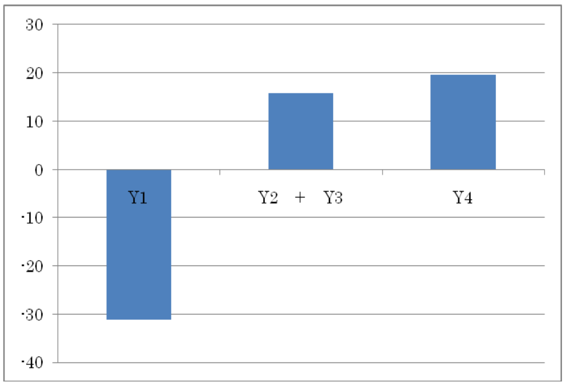
Table 14: Impact Degrees of Determinants in Equation (15)



6 Conclusion

Remedial Education is an urgent demand of the rapid development of higher education. It is a prerequisite for potentially productive higher education, and how to help students pull up their academic proficiencies up to a desirable level within a limited time span works as the key. How to increase the effectiveness of remedial education is a common problem that more and more countries, especially developed countries or areas will have to face in the near future.

Table 15: Auxiliary Analysis of Impact Degrees of Determinants in Equation (15)



Since remedial education course parallels the normal curriculum study in Japanese colleges/universities, it requires a most dramatic efficacy in its implementation process. Education production is an indication which represents the consequence of the complex function of numerous factors. The key component in the solution of this problem is how to spot those determinants related to the result of remedial education and figure out how they contribute to the cause.

English remedial education is exclusively determined by factors of three aspects – students' total academic commitment, correct understanding and active attitude toward intercultural communication and admirable computer operation skills. Rather than how much time they spend with the online learning tool, how much they are willing and determined to get involved in the total school learning activity seems to influence their post-course test performance most seriously. Although cognitive factors are striking in our analysis, student's computer operation skill is a third index explicating the prediction model (equation 4). It may not demonstrate distinctness in other education environment where computer is not applied as the principal learning tool.

The adaptive model (equation 15) provides a broader scope of viewing the issue and settles the problem by confirming that students' psychological processes function as the key determinant in improving the quality of their learning model and their positive attitudes toward remedial course help prompt a more preferable consequence. This finding accords with many studies stressing the importance of students' cognitive understanding about remedial courses [18] [4].

Low proficient students usually lack motivation, confidence and self-regulatory efficacy. They show comparatively less intended efforts in learning, fail to carry out the original learning plans and tend to be the dropouts. But they are required to be responsible for their own study and manifest self-regulatory efficacy through self-observation, self-judgment and self-response in a web-based learning environment. How to help them obtain sense of achievements form learning activities is a topic which needs to be discussed in detail. In sum, exploring students' cognitive attitudes has more in-depth implication in remedial education through online learning [19].

7 Reference

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