Journal of
Social and Administrative Sciences
www.kspjournals.org
Volume 4 December 2017 Issue 4

The factors affecting of digital mobile e-learning on development in senior high schools

By Hsiang-Hsi LIU [a] & Fu-Hsiang KUO [b†]

Abstract. The traditional data envelopment analysis (DEA) model ignores the cooperative relationship among decision-making units (DMUs), so it is difficult to evaluate the DMUs efficiency reasonably. In this study, we use a cross-efficiency and Bootstrap Truncated Regression (BTR) model to analyze the effect of digital mobile e-learning on school efficiency. The empirical results of this research indicate the following results: (1) Importing digital mobile e-learning can really enhance the efficiency of school management. (2) The school size, tablet PC numbers, total equipment expenses associated with tablet PC and school location are important determinants for affecting the efficiency of school management. Owing to the government is full implementation of the new learns model, that is, to be where the students able to experience the authentic joy of new learning model and attract students join. The result of the study suggested that in order to increase the school's cross-efficiency model efficiency. The first assist the school in upgrading the Wi-Fi technology and network equipment. In general, the school adds to the Wi-Fi technology and network equipment. That would enlarge the school network and as to attract more school will adopt the new learning. It is where the students able to experience the authentic joy of new learning model and attract students join. Thus, the schools will increase school size. However, it should be noted that total equipment expenses associated with tablet PC have the negative influence on school management efficiency due to the increasing costs for furnishing the related internet and network equipment or device to facilitate for teaching and learning among teachers and students by digital mobile e-learning. The results of this research can also be the reference for educational authorities when formulating policies and regulations for promoting digital mobile e-learning in high school in Taiwan.
Keywords. Operating efficiency, Digital mobile e-learning, Data envelopment analysis (DEA), Truncated bootstrapped regression (TBR), Cross efficiency model.
JEL. I21, I25, I28.

1. Introduction

The fast advancement of information technology and continuous improvement of digital mobile e-learning (such as smart phones, PDAs, and tablets) in recent years have contributed to a steady growth of software and hardware development for digital learning technology. Furthermore, the M-learning types are integrated tools which provide teaching aids for current and future era. Therefore, technology is playing a pivotal role in digital mobile e-

[a] Graduate Institute of International Business, National Taipei University, New Taipei City, Taiwan.
☎. + 886-2-25021520
✉. hsiang@mail.ntpu.edu.tw
[b†] Department of Information Management, Chaoyang University of Technology, Taichung City, Taiwan.
☎. +886-4-23323000 ext.7122
✉. s1185072@gmail.com

learning today, and has allowed teachers to experience the importance and emerging trend of combining technology with instruction in the classroom.

As the digital mobile e-learning to teach is importance and emerging trend in the classroom. Hence, the Department of Education collaborated with grassroots foundations (HTC Company) in September, 2012 and donated 6,500 tablets first to the freshmen and teachers at six senior high schools in Taipei, in order to promote digital mobile e-learning by incorporating e-teaching platforms. By 2017, there were more than 100 schools in the country to use tablets for learn, which allowed students and teachers in various counties and cities to develop digital mobile e-learning by utilizing wireless networks to enhance teaching quality and increase students' interest level.

On the other hand, the population as for the basic elements of the composition of the population, the number of population and age structure changes always to determine the key to the development of the country. Unfortunately, the government has not seriously tackled the population problems in the past few years in Taiwan. This recruitment crisis has been faced by many vocational and senior high schools in Taiwan, especially the private Vocational and Senior High Schools bearing the brunt of the lack of business opportunities. Due to the decline and change in the fertility rate of the population of Taiwan, resulting change population structure in Taiwan. This problem will affect many aspects, such as country, business, education, family, and individual. In education, the most direct impact on the school is the lack of students and cause the school of a decrease in student enrolment. Even more worrying is that after three years, the number of junior graduate students will be reduced from 300,000 to 190,000 in Taiwan. Its problem will lead to the management difficulties of the school and face closure of schools. Thus, the education needs continuously improve to meet the demands exerted by social change and national development. As mentioned above, the studies of the analysis of school competitiveness is long being the important issues at the industry, government, and academic levels. Only by enhancing the school competitiveness, schools can continue to operate.

In recent years, schools in various counties and cities in Taiwan have gradually introduced education reforms and innovative teaching such as mobile digital learning. A good deal of literature has reported that digital mobile e-learning can increase students' interest in learning as well as their motivation to learn. However, whether the high schools that have introduced mobile digital learning to enhance classroom teaching, increase in-classroom learning effectiveness, attracting student attendance, and in turn raising schools' operational efficiency remains a topic not yet widely addressed in the literature published domestically. Relevant theoretical foundations are likewise not widely. Hence, what prompted the undertaking of the current study was to better understand the actual teaching in the field by analyzing appropriate cases where schools have embarked on initiatives to improve themselves, and to derive suitable policy recommendations. Specifically, we firstly applies data envelopment analysis (DEA) and cross-efficiency model to analyze the schools' operational of high school in this study and justify whether mobile digital learning can affect a school's cross-efficiency model efficiency by Truncated Bootstrapped Regression (TBR).

The paper is structured as follows: Section 1 introduce the research background and goal of the research, Section 2 begins with a brief review of e-learning, Section 3 reviews the DEA method, Section 4 explains the empirical analysis, and the Section 5 concludes our research results.

2. Literature review

In general, the digital mobile e-learning that refers to a subset of E-Learning, educational technology, and distance education, that focuses on learning across contexts and learning with mobile devices. The digital mobile e-learning has many different definitions and is known by many different names, like M-Learning, U-Learning, personalized learning, learning while mobile, ubiquitous learning, anytime / anywhere learning, and handheld learning. One definition of mobile learning is, "any sort of learning that happens when the learner is not at a fixed, predetermined location, or learning that happens when the learner takes advantage of the learning opportunities offered by mobile technologies" (O'Malley *et al.,* 2005). In other words, with the use of mobile devices, learners can learn anywhere and at any time (Crescente & Lee, 2011).

The digital mobile e-learning is considered to be the ability to use mobile devices to support teaching and learning. Hence, the digital mobile e-learning devices are increasingly presented as tools that support transitions between episodes of learning in formal and informal settings, or simply as a means of supporting and connecting a student's learning whether it be formal or informal. Furthermore, the digital mobile e-learning focuses on the mobility of the learner, interacting with portable technologies, and learning that reflects a focus on how society and its institutions can accommodate and support an increasingly mobile population. This is because mobile devices have features and functionality for supporting learners. For example, podcasts of lectures can be made available for downloading. Learners are to expect to engage with these learning resources whilst away from the traditional learning spaces. Over the past ten years the digital mobile e-learning has grown from a minor research interest to a set of significant projects in schools, workplaces, museums, cities and rural areas around the world. Thus, in the past few decades, the digital mobile e-learning model is still of such differences, with different national perspectives, differences between academia and industry, and between the school, higher education and lifelong learning sectors (Singh, 2010). As for example in the implementation of virtual classrooms (Dawabi *et al.,* 2004), using experimental methods of teaching scientific and practical knowledge across many educational channels (Milrad *et al.,* 2004). In fact, the digital mobile e-learning model can also create and share their knowledge through blogs and interactive games installed on their smart phone devices, and the digital mobile e-learning provides appropriate tools for exchanging ideas and voting through integrative online classroom management systems (Goh & Kinshuk, 2006). Also, the digital mobile e-learning can also help users to deal with data and charts. The ability to access information at any time and in any place represents a significant advantage of M-learning, again confirming that it is an extension and newly learned skill of the digital mobile e-learning rather than a subset of it (Badri & El, 2012; Wang *et al.,* 2009).

On the other hand, the Data envelopment analysis (DEA) model, proposed by Charnes, Cooper, & Rhodes (1978), the model is essentially a linear programming model to evaluate efficiencies of decision-making units (DMUs) by calculating the best multiplier for inputs and outputs. Because it deals with multiple inputs and outputs advantage without assuming any particular functional frontier form, literally thousands of articles have been published in this field, it has been widely applied in many different research fields. Such as resource-allocation (Du *et al.,* 2014), professors work (Oral *et al.,* 2015), athletes efficiency (Oukil & Amin, 2015), academic departments (Wu *et al.,* 2012) , nursing homes (Wu *et al.,* 2016b) and the operating efficiency of vocational and senior high schools (Liu *et al.,* 2016).

As mentioned above, the DEA model has been widely used for is a non-parametric statistical method for assessing the production frontier of DMUs and evaluating their relative efficiencies, has been proven an effective approach in identifying best practice frontiers, but its flexibility in weighting multiple inputs and outputs and its nature of self-evaluation have been criticized. Hence, the cross efficiency method was developed as a DEA extension to rank DMUs (Sexton *et al.,* 1986), with the main idea being to use DEA to do peer evaluation, rather than to have it operate in a pure self-evaluation mode. Thus, the traditional DEA models cannot rank all DMUs fully, especially the more efficient DMUs (Wang & Chin, 2010). On the contrary, the cross efficiency model has been further investigated by Doyle & Green (1994), and to present two advantages of the cross-evaluation method. First, the cross efficiency model provides an ordering among DMUs. Secondly, the cross efficiency model eliminates unrealistic weight schemes without requiring the elicitation of weight restrictions from application area experts. Thus, the Cross efficiency evaluation model has been used in various applications, e.g., efficiency evaluations of nursing homes (Sexton *et al.,* 1986), efficiency evaluation sin public procurement tenders (Falagario, *et al.,* 2012), evaluation of China's electric energy (Chen *et al.,* 2017), and others.

As mentioned above, our literature review revealed that the standard DEA (CCR and BCC models) models were most often used for performance evaluation. The inputs mainly included human resources (teachers, staff members, and students), financial resources, material resources (equipment and books), and space resources (campus size). The outputs mainly included teaching functions (the current number of students, graduates, and certificate holders), research functions (the number of research projects, awards, and published articles), education and employment opportunities (enrollment rates, number of graduates, number of dropouts, and number of people employed), student behavior (the number of students rewarded and/or punished), and other items (e.g., the number of times books or CDs were borrowed).

We know that the mobile learning can happen anywhere: in a classroom, at the dining room table, on a bus, in front of a science exhibit, and anywhere. Portability is not as important as the ability of the learner to connect, communicate, collaborate, and create using tools that are readily at hand. In fact, the education reforms coupled with innovative teaching which incorporates digital mobile e-learning can indeed increase students' interest in learning and their motivations (Liu & Kuo, 2017a; Liu & Kuo, 2017b). However, there have been limited related research published domestically or overseas and scanty theoretical discourses on topics such as whether the school that introduces digital mobile e-learning can capitalize on such initiatives to enhance teaching and increase the school's competitiveness. Hence, what prompted the undertaking of the current study was to better understand the actual teaching in the field by analyzing appropriate cases where schools embarked on applying to digital mobile e-learning. We hope that the results of this study can serve as a reference for schools setting up their performance improvement strategies and for government agencies in formulating related policies and measures.

Based on the above literature review, for this study that the following research hypotheses are proposed and the description is as follows:

3. Study model

The purpose of this research is to analyze whether really improve the efficiency of school management that implemented digital mobile e-learning and teaching in an attempt to determine whether the operational efficiencies of these schools were significantly improved following digital mobile e-learning introduction. Hence, in the present study, we opted for the cross efficiency model approach because our goal was to unravel efficiencies of school managements using a unique efficiency index and uses TBR to analyze that factors affecting the relative efficiencies of schools in various counties and cities by utilizing related factors as explanatory variables.

3.1. DEA

The DEA model, proposed by Charnes *et al.,* (1978) and known as CCR, assumes the DMUs to be assessed operate within a technology where efficient production is characterized by constant returns to scale(CRS).As above is obtained from the following Equation (1):

$$\text{Max } h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \tag{1}$$

$$s.t \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad , \quad j = 1,\ldots,n$$

$$u_r, v_i \geq \varepsilon > 0, \quad r = 1,\ldots\ldots.,s, \quad i = 1,\ldots\ldots.,m$$

where C is the amount of the i-th input to DMU j, y_{rj} is the amount of the r-th output to DMU j; C are called r virtual multiplier output and i virtual input multiplier; The value of Cobtained is termed the relative efficiency and is called the CCR efficiency, the ε is a non-Archimedean positive element smaller any real number (10^{-6}), the CCR model is called non-Archimedean small number.

Banker *et al.,* (1984) modified this basic model to permit the assessment of the productive efficiency of DMUs where efficient production is characids by variable returns to scale (VRS). The VRS model, known as BCC, differs from the basic CCR model only in that in includes in the previous formulation the convexity constraint:

$$\sum_{i=1}^{n} \lambda_j = 1$$

In summary, the following equation can be obtained for computing efficiencies:

Total (Technical) Efficiency (TE) = Pure Technical Efficiency (PTE) × Scale Efficiency (SE)

However, using traditional DEA models to evaluateefficiency has certain deficiencies. For example, some DMUs cannot be ranked fullyusing traditional DEA models. To solve such problems, the cross-efficiency evaluationmethod has been proposed to replace the self-evaluation system.

3.2. DEA cross-efficiency (DEA-CE)

The cross-efficiency model, proposed by Sexton *et al.,* (1986), the main idea of cross-efficiency evaluation is to use DEA in a peer-evaluation called of a self-evaluation model. The cross-efficiency method simply calculates the efficiencyscore of each DMU n times, using the optimalweights evaluated by the n LPs (linear program). Based on above Equation (1), by comparing operational efficiency for DMU between self (kk) and peer (kj), the following Equations (2) and (3) can be constructed to help cross-efficiency evaluation such as $E_{KK}$and E_{Kl}:

$$max \quad E_{kk} = \frac{\sum_{r=1}^{s} u_{rk} y_{rk}}{\sum_{i=1}^{m} v_{ik} x_{ik}} \tag{2}$$

$$s.t. \quad E_{kl} = \frac{\sum_{r=1}^{s} u_{rk} y_{rl}}{\sum_{i=1}^{m} v_{ik} x_{il}} \leq 1$$

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1 \quad l \neq k \quad r = 1,\ldots\ldots.,s, \quad i = 1,\ldots\ldots.,m$$

$$min \quad M_k = \sum_{l=1, l \neq k}^{m} E_{kl} \Big/ (m-1) \tag{3}$$

Among E_{kk} is called self-evaluation, E_{kl} is called peer-evaluation, M_k and is called the average efficiency value ofpeer-evaluation. Where cis the amount of the i-th input to DMU j, y_{rj} is the amount of the r-th outputto DMU j; u_r, v_i are called r virtual multiplier output and i virtual input multiplier; The value of cobtained is termed the relative efficiency and is called the CCR efficiency, the$\varepsilon$is a non-Archimedean positive element smaller any real number (10^{-6}).

It need to note that although DEA might be an approach in identifying best practicefrontiers, its flexibility in weighting multiple inputs and outputs and its nature ofself-evaluation have been criticized. The cross-efficiency method was developed asa DEA extension to rank DMUs (Sexton *et al.,* 1986), with the main idea being touse DEA to do peer evaluation, rather than to have it operate in a pure self-evaluationmode. In our study, a topic of interesting in efficiency analysis to compare the vocational School with senior High School can be justified by cross-efficiency (self-peer evaluation efficiency) model.

3.3.Truncated bootstrapped regression (TBR)

As the efficiency rate derived from DEA is often the function of influential variables such as DMU characteristics, region, attribute and other environmental variables are usually used to describe factors which could influence the efficiency of DMUs. In this study, such factors are not traditional inputs and are assumed to be outside the control of the DMUs. Since the sensitivity analysis proposed by Charnes, *et al.,* (1994) to test the consistency of the results calculated based on DEA. However, this sensitivity analysis is still unable to show the degree of effect of input or output variables on the calculated efficiencies. As a result, we used the Truncated Bootstrapped Regression belongs to the limited dependent variable or truncation econometrics model, with the nature of limited values of dependent variables relating to the actual observed explanatory variables (Celen, 2013).

The standard Tobit regression model (TRM, also known as truncated or censored regression model) indicated by Tobin's (1958) can be outlined as following Equation (4) for that $y_i^*$is observed if $y_i^* > 0$ and is not observed if $y_i^* \leq 0$.Then the observed y_i will be defind as:

$$y_i = \begin{cases} y^*_{i=\beta x_i + u_i} & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \tag{4}$$

$$u_i \sim \text{IN}\,(0, \sigma^2)$$

Where $u_i \sim \text{IN}\,(0, \sigma^2)$, x_i and β are vectors of explanatory variables and unknown parameters, respectively, while y_i^* it is a latent variable and y_i is the DEA efficiency scores. When the DEA scores are transformed, the coefficient of the Tobit regression model can be interpreted as if it is a coefficient of the maximum likelihood estimation (MLE). That is, it indicates the expected proportionate change of dependent variable with respect to one unit change in independent variable Xi, holding other factors constant. In this study, we employ Tobit regression analysis to examine the effects of explanatory variables including digital mobile e-learning factors.

A common practice in the DEA literature for estimating model (2) had been to employ the Tobit-estimator until Simar & Wilson (2007) demonstrated that such an approach was inappropriate. Instead, they justified an approach based on a truncated-regression with a bootstrap and illustrated (in Monte Carlo experiments) its satisfactory performance. The adequacy of the functional form to the data is a prevalent problem and a common critique of the stochastic frontier models (Khumbakar & Lovell, 2000). Here, we employ the Simar & Wilson (2007) approach. The standard Truncated Bootstrapped Regression model (TBR) indicated by Simar & Wilson (2007) can be outlined as following Equation (5). Formally, our econometric model is given by:

$$y_i = \begin{cases} \hat{y}_i \approx \beta x_i + u_i & \text{if } \hat{y}_i > 0 \\ 0 & \text{if } \hat{y}_i \leq 0 \end{cases} \quad (5)$$
$$u_i \sim \text{IN}\,(0, \sigma^2)$$

Where $u_i \sim \text{IN}\,(0, \sigma^2)$, x_i and β are vectors of explanatory variables and unknown parameters, respectively, while $\hat{y}_i$ it is a latent variable and y_i is the DEA efficiency scores. Relying on asymptotic theory, normal tables can be used to construct confidence intervals. However, the construction can be more precise if the bootstrap is used, particularly because of our regress and are not true variables and their estimates that are likely to be dependent on observed variables (Simar & Wilson, 2007).

3.4. Variance inflation factor

Proposed by Farrar & Glauber in (1967), the Variance Inflation Factor (VIF) measures the inflation of the parameter estimates being computed for all explanatory variables in the model. The VIF formula is as follows Equation (6):

$$\text{VIF}=\frac{1}{R_j^2} \text{ , 1, 2,..., m}$$

Where is R_j^2 the Coefficient of Determination for the explanatory variable.

In this research, VIF is calculated for each explanatory variable and it is used to assess the correlation of each explanatory variable with the other variables in the model. When the value of the coefficient of determination R_j^2 is close to or equal to one, it indicates the presence of multicollinearity between explanatory variables, which makes the value of VIF large. On the other hand, when the variable X_j is independent of the rest of the other explanatory variables, the value of the coefficient of determination is;

R_j^2= 0 and this leads to: VIF=1

Researchers such as Farrar & Glauber (1967) have shown that if VIF ≥ 10, this indicates the presence of multicollinearity between explanatory variables. Thus, this means that there is multicollinearity between these explanatory variables and to delete the variables.

4. Empirical results and analysis

The empirical analysis of this study mainly comprised two parts: firstly, this section will adopt the cross-efficiency methodto analyze the relative efficiencies of schools analysis method. Followed by the application of the cross-efficiency method and furthermore, this study applies Tobin regression model to analyze the factors which include digital mobile e-learning factors that affecting the relative efficiencies of schools in New Taipei.

4.1. Results of efficiency analysis for cross-efficiency method

The efficiency analysis of this study mainly comprised three main sections. Section 1 describes the study objects and variable for inputs and outputs in this study. Section 2 presents data description and correlation analysis between inputs and outputs. Finally, Section 3 analyzes the efficiency analysis of the cross-efficiency method.

4.1.1 Research subject

The research subjects of this study consist primarily of vocational and senior high schools in the Xindian District of New Taipei City. The nine schools were divided into two groups, to represent the characteristics of (1) the vocational schools and (2) senior high schools. The names and characteristics of the schools are provided in Table 1.

Table 1. *School names and characteristic*

NO	School name	nobile e-learning(ME)	Cityname	Group
1	Taipei First Girls High School	Yes	Taipei	2
2	Taipei Municipal Fuxing Senior High School	Yes	Taipei	2
3	Taipei Municipal Lishan Senior High School	Yes	Taipei	2
4	Taipei Municipal Yang Ming Senior High School	Yes	Taipei	2
5	Taipei Municipal Zhong-Lun Senior High School	Yes	Taipei	2
6	Juang Jing Vocational High School	Yes	New Taipei	1
7	Chi Jen Senior High School	Yes	New Taipei	2
8	National Lo-Tung Senior High School	Yes	I lan	2
9	National Hualien Industrial Vocational Senior High School	Yes	Hualien	1

Note: group 1 indicated the vocational high school group; Group 2 indicated senior high school group.

4.1.2. Variables

Prior to the establishment of the empirical model, we list as many preliminary assessment factors as possible for the input and output units. Any variable that may affect the DMU performance dimension is included for investigation, so that no pre-setting of output function type was required. After referring relevant literatures (Lee, & Huang, 2012) and statistical reports, we select the following three operational variables as inputs for public and private vocational and senior high schools, namely number of department, number of teachers and number of staff. And 3 outputs, namely the number of school students, number of graduate and number of classes. Pearson's correlation analysis is then used for preliminary analysis of the level of correlation between the inputs and outputs (Table 2).

Table 2. *Seven major indicator definition for inputs and outputs*

NO	Indicators	Code	Definition
1	academic department	x_1	Total academic department of the school.
2	number of full-time teachers	x_2	The total number offull-time teachers.
3	number of part-time teachers	x_3	The total number of part-time teachers.
4	staff	x_4	The total number of staffs.
5	number of school students	y_1	the number of school students
6	graduate student	y_2	The number of graduate students.
7	classes	y_3	The number of school classes.

Table 3. *DEA Model Input and Output Indicators Definitions*

NO	Indicators	Code	Definition
1	academic department	x_1	Input Indicator
2	number of full-time teachers	x_2	Input Indicator
3	number of part-time teachers	x_3	Input Indicator
4	staff	x_4	Input Indicator
5	number of school students	y_1	Output Indicator
6	graduate student	y_2	Output Indicator
7	classes	y_3	Output Indicator

4.1.3. Data descriptions and correlation analysis between inputs and outputs

The section is divided into two main sections. Section 1 describes data descriptions. Section 2 presents the correlation analysis between inputs and outputs in this study.

Data descriptions

Descriptive statistics were calculated. Ultimately, data was collected on several variables of interest for 27 out of the 9 schools for three (2013-2015) years. The list of variables and their summary statistics are presented listed in Table 4.

Table 4. *Descriptive statistics*

Code	Minimum	Maximum	Mean	SD	Variance
x_1	1.00	3.00	1.78	0.93	0.87
x_2	70.00	195.00	143.11	38.97	1518.64
x_3	1.00	73.00	17.70	19.62	385.06
x_4	17.00	80.00	30.59	16.87	284.64
y_1	723.00	4729.00	1962.33	1115.21	1243700.77
y_2	294.00	1146.00	598.96	274.68	75447.96
y_3	18.00	109.00	53.19	25.77	664.00

Correlation analysis between inputs and outputs

This study employed Pearson correlation analysis to first analyze the degree of correlation between input and output variables and removed variables with negative correlations. Another correlation analysis was then conducted to ensure positive correlations between the variables selected and adherence to the estimation principle of DEA model. Finally, the results showed that the input variables chosen were the number of teachers, the number of part-time teachers, and the number of faculty and staff, while the output variables were chosen were the total population of the school, the number of graduates, and the number of graduating classes. The results of the final correlation analysis are displayed in Table 5.

Table 5. *Correlation test and analysis*

	x_2	x_3	x_4	y_1	y_2	y_3
x_2	1	.421	.528	.819	.825	.815
x_3		1	.855	.775	.583	.773
x_4			1	.792	.567	.761
y_1				1	.905	.978
y_2					1	.867
y_3						1

4.1.4. Efficiency analysis

Regarding efficiency analysis is divided into three Section. Section 1 DEA Analysis. Section 2 DEA Cross-Efficiency analysis. Finally, Section 3 Integrative analysis of the two models.

DEA of technical (total) efficiency (TE) analysis

As shown in Table 6 below after imported digital mobile e-learning. Since the introduction of digital mobile e-learning in 2012, there have three schools reached an overall technology efficiency rate of "1" for three years in a row, respectively the Taipei First Girls' High School, Taipei Municipal Fuxing Senior High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School etc. On the other hand, the remaining five schools failed to reach the efficiency rate of "1", including the National Hualien Industrial Vocational High School, Chi Jen High School, National Lo-Tong Senior High School, National Yang Ming Senor High School, and Taipei Municipal Zhong-Lun High School. This result demonstrates that the introduction of digital mobile e-learning does not necessarily affect a school's operational efficiency in spite of the school's more robust connection to the network. For example, the operational efficiency of the Taipei Municipal Zhong-Lun High School is actually lower than that of other schools, despite the introduction of digital learning during 2013 and 2014.

Table 6. *Total efficiency analysis of high schools in this study*

DMU	2013	2014	2015	Average	Ranking
1	1.000	1.000	1.000	1.000	1
2	1.000	1.000	1.000	1.000	1
3	0.838	0.848	0.796	0.827	8
4	1.000	1.000	0.955	0.985	5
5	1.000	1.000	1.000	1.000	1
6	1.000	0.784	0.758	0.847	7
7	1.000	1.000	0.797	0.932	6
8	0.578	0.637	0.985	0.733	9
9	1.000	1.000	1.000	1.000	1

DEA coss-efficiency of schools

The primal goal of the cross-efficiency model (DEA-CE) developed by Sexton *et al.,* (1986) is to maximize the self-assessment efficiency, and its secondary goals are to minimize the average efficiency value from peer assessment. Specifically, phase 1 is the self-evaluation phase where DEA scores are calculated using the constant returns-to-scale (CRS) DEA model of Charnes *et al.,* (1978). In the second phase, the multipliers arising from phase 1 are applied to all peer DMUs to arrive at the so-called cross evaluation score for each of those DMUs. The results of the estimation are shown in Table 7.

Table 7. *Efficiency valuesforeach year underthe DEA-CE Model*

DMU	2013	2014	2015	Average	Ranking
1	0.993	0.998	0.982	0.991	2
2	0.979	0.967	0.936	0.961	3
3	1.000	1.000	1.000	1.000	1
4	0.855	0.826	0.788	0.823	7
5	0.682	0.666	0.720	0.689	9
6	0.880	0.890	0.868	0.879	4
7	0.895	0.849	0.887	0.877	5
8	0.947	0.799	0.754	0.833	6
9	0.711	0.700	0.674	0.695	8

As shown in Table 7 below under the DEA-CE model. Since the introduction of digital mobile e-learning in 2012, the Lishan Senior High School is only one reached an overall technology efficiency rate of “1” for three years in a row. According to the holistic acceptabilityscores of the DMUs, a full and unique ranking among these nine schools departments is listed as $DMU_3 > DMU_1 > DMU_2 > DMU_6 > DMU_7 > DMU_8 > DMU_4 > DMU_9 > DMU_5$. In truth, their efficiencies were generally low under the DEA-CE model. The main reason for considering the relationship between peer to peer. If the causing total efficiency to fall below 1, the school resources showed may have been over utilized or inadequate resources. The DEA-CE model results in Table 7.

Comparison analysis of the two models

This DEA model has been proven an effective approach in identifying best practice. Conversely, this approach in itself was criticized for flexibility in weighting multiple inputs and outputs and its nature of self-evaluation. On the other hand, both traditional DEA models has manydisadvantages in sequencing efficiency values. For example, traditional DEA modelscannot rank all DMUs fully, especially the more efficient DMUs (Wang & Chin, 2010). See, for example, in Table 6 under the DEA model. Since the introduction of digital mobile e-learning in 2012, the four schools have reached an overall technology efficiency rate of “1” for three years in a row. Thus, the traditional DEA models really cannot rank all DMUsfully, mainly attributable to the self-evaluation system of traditional DEA model leads to large and not objective evaluation results, resulting mainly from it does not consider self-evaluation relationship between DMUs.

Table 8. *Comparison analysis of the two models*

DEA model					DEA-CE model			
DMU	2013	2014	2015	Ranking	2013CE	2014CE	2015CE	Ranking
1	1	1	1	1	0.993	0.998	0.982	2
2	1	1	1	1	0.979	0.967	0.936	3
3	0.838	0.848	0.796	8	1.000	1.000	1.000	1
4	1	1	0.955	5	0.855	0.826	0.788	7
5	1	1	1	1	0.682	0.666	0.720	9
6	1	0.784	0.758	7	0.880	0.890	0.868	4
7	1	1	0.797	6	0.895	0.849	0.887	5
8	0.578	0.637	0.985	9	0.947	0.799	0.754	6
9	1	1	1	1	0.711	0.700	0.674	8

We have presented the DEA-CE model to improve the DEA mode shortcomings. The DEA-CE model results in Table 7. The results show a new rank all DMUs, these nine schools departments is rank as $DMU_3 > DMU_1 > DMU_2 > DMU_6 > DMU_7 > DMU_8 > DMU_4 > DMU_9 > DMU_5$. Thus, the results show the DEA-CE model ready to improve the DEA mode shortcomings, give a new rank all DMUs. Our result is consistent with Sexton *et al.,* (1986) justified and the comparisons analysis of the two model results in Table 8.

4.2. Results of truncated bootstrapped regression (TBR)- explaining the determinants affecting cross-efficiency

To discuss the results for Tobit Regression Analysis. Section 1 describes the model setups including regression variable and parameter setting for TBR. Section 2 discusses the empirical results of TBR.

To analyze determinants of efficiency, we follow the two-step approach as suggested by Coelli *et al.,* (2005) by regressing the efficiency scores against a set of environmental variables of a nondiscretionary nature. It is well documented in the DEA literature that the efficiency scores obtained in the first stage are correlated with the explanatory variables used in the second stage, which makes the second-stage estimates inconsistent and biased. Hence, the use of Simar & Wilson's (2007) truncated regression analysis to overcome this problem.

The purpose of this based on the related theories and literature provided useful information in this study, it is indicated that the variables usually be used related researchers, and we focus the major variables that relate to the determinants of mobile digital e-learning. To this end, as explained earlier, we adopt the approach of Simar & Wilson (2007). The research of this basic model setups can be described and the estimated specification for the regression is expressed as follows:

A. Model setups for the factors affect DEA-CE of school

Basic model setups can be described as following Equation (7):

$$CE_{it} = f(Z1_{it}, Z2_{it}, Z3_{it}, Z4_{it}, xZ5_{it}, Z6_{it}, Z7_{it}, Z8_{it}) \quad (7)$$

The statistical model can be written as follows (Equation (8)):

$$CE_{it} = \beta_0 + \beta_1 Z1_{it} + \beta_2 Z2_{it} + \beta_3 Z3_{it} + \beta_4 Z4_{it} + \beta_5 Z5_{it} + \beta_6 Z6_{it} + \beta_7 Z7_{it} + \beta_8 Z8_{it} + \varepsilon_{it} \quad (8)$$

The theoretically expected signs of the coefficients are:

$\beta_1>0, \beta_2>0, \beta_3>0, \beta_4>0, \beta_5>0, \beta_6>0, \beta_7>0, \beta_8>0$

Where

CE_{it}: Cross-Efficiency for management of School i during the period 2013 to 2015

$Z1_{it}$:School size (total numbers of school students) of School i

Z_{2it}: Teacher-student ratio (average number of students per teacher members) of School i
Z_{3it}: The total number of tablet PC of School i
Z_{4it}: Technical teacher ratio (measured by the ratio for the numbers of technicians as consultants for teaching tablet PC knowledge to total number of teachers in school) of School i
Z_{5it}: Total equipment expenses associated with tablet PC of School i
Z_{6it}: School location dummy: in the northern area: 1, other areas: 0
Z_{7it}:School attribute dummy: public high schools: 1, private high schools: 0
Z_{8it}: School attribute dummy: senior High School: 1, vocational high schools: 0
ε_{it}: Disturbance terms, $\varepsilon_{it} \sim$iid N $(0,\sigma^2)$

Detecting the multicollinearity problems

The measures used for testing the existence of the multicollinearity in the model are, as previously described, VIF. These indicators were computed for the regression parameters of all the explanatory variables of the model. The multicollinearity between the explanatory variables was revealed, as proven by the following results:

Table 9. *Variance inflation factors*

Variance	Variance Inflation Factors
CE	0.186
Z_1	0.005
Z_2	12.28
Z_3	$5.17 * 10^{-7}$
Z_4	0.023
Z_5	0.007
Z_6	0.002
Z_7	10.23
Z_8	14.28

We notice from Table 9 that the values of the VIF for some of the explanatory variables (Z_2, Z_7, Z_8) are greater than 10 and these variables suffer from inflation in the variance of their parameters: three variables are the cause of the multicollinearity problem and to delete the variables.

Truncated Bootstrapped Regression: Explaining the Determinants Affecting Cross-Efficiency

In this study, we use panel data (time series and cross-section data) to estimate how each factor including digital mobile e-learning affectingcross-efficiency. Panel data may have group effects, time effects or both. These effects are either fixed effect or random effect. A fixed effect model assumes differences in intercepts across groups or time periods, whereas a random effect model explores differences in error variances. Given the panel nature of the dataset, a Hausman specification test was run to determine whether the Fixed Effects (FE) or the Random Effects (RE) model was best suited for the data (Hausman, 1978). In this test, Prior the estimation for Equations (5), the Hausman test (p value= 0.0054) shows that the p value is less than 0.05 which is significant. Therefore, the fixed effect model is preferred model and will be used in this study. This research investigates the factors affecting the TE based on a sample of 27 schools over the period 2012-2015. Table 9 reports the regression results through the maximum likelihood estimation (MLE) for the dynamic panel data model with fixed effect to analyze the factors affecting the cross-efficiency (CE).

As indicated in Table 10, we can find firstly that School size (β_1=-0.691***), Tablet PC numbers (β_3=-0.005***), Total equipment expenses associated with tablet PC(β_5=5.4×10^{-7}***) and School location (β_6=0.081***) are important determinants for affecting efficiency of school management.

Table 10. *The determinants affecting cross-efficiency*

Variable		β(Beta)	Std. Error	t-vaule	P value
Constant	β_0	4.758***	0.548	8.703	0.000
Z_1	β_1	-0.691***	0.088	-7.840	0.000
Z_3	β_3	-0.005***	4.5×10^{-4}	-10.085	0.000
Z_4	β_4	-5.1×10^{-5}	0.0003	-0.128	0.898
Z_5	β_5	5.4×10^{-7}***	4.53×10^{-8}	10.292	0.000
Z_6	β_6	0.081***	0.023	3.361	0.008
Likelihood			48.413***		
Wald Test			*14.17****		
Durbin Watson Test			*1.913*		
White Test			*9.005*		
ARCH Test			*4.03*		

Note:*p<0.10;**p<0.05;***p<0.001

The results

(1) School size (Z_1)

According to the empirical results shown in Table 9, the effect of school size (β_1=-0.691***) on school's cross-efficiency model efficiency in the model has significant 5% level but positive relationship as indicated in Table 9. Owing to the government is full implementation of the new learns model, that is, to be where the students able to experience the authentic joy of new learning model and attract students join. Thus, it is generally considered that the more Tablet PC numbers to be applied in high school will cause the school's cross-efficiency model and then cause school's cross-efficiency model efficiency. Since the full implementation of the new learns by the government will not vary depending on the number of students in school. It will not affect digital mobile e-learning, but not the main determinant. Because the result of tablet PC numbers is not support. The sign is not consistent with Ozdamli & Cavus (2011).

(3) Tablet PC numbers (Z_3)

As can be seen that the results shown in Table 9. The effect of tablet PC numbers (β_3= -0.005) on school's cross-efficiency model efficiency in the model has the significant 5% level but the positive relationship as indicated in Table 9. On school's cross-efficiency model efficiency in the model has the significant but positive relationship as indicated in Table 9. Owing to the government is full implementation of the new learns model, that is, to be where the students able to experience the authentic joy of new learning model and attract students join. Thus, the tablet PC numbers addition and it will affect the school's cross-efficiency model efficiency, reduce the increase by 0.05% and it the main determinant. This research is the result of tablet PC numbers is supported. The sign is consistent with Ozdamli & Cavus (2011).

(4) Technical teacher ratio (Z_4)

According to the estimated results shown in Table 9. The effect of technical teacher ratio (measured by the ratio for the numbers of technicians as consultants for teaching tablet PC knowledge total number of teachers in school) (β_4= -5.1×10^{-5}) on school's cross-efficiency model efficiency in the model has the non-significant and positive relationship as we expected. In these settings, the role of the teachers needs to change from the presenter of expert knowledge to a moderator of opposing positions. In this role, teachers act as technicians as consultants for teaching tablet PC knowledge need to be able to identify the students' interests, relate these interests to the topic related learning goals, and offer opportunities to reach these goals that are related to the specific conditions a learner is in. In general, when an increase in the technical teacher ratio, even more, school students to apply for this digital mobile e-learning program, when ratio for the numbers of technicians as consultants for the teaching tablet PC knowledge total number of teachers in school expand, they are able to cause school's cross-efficiency model efficiency. Today, Owing to the reduction in the number of students per class, technical staff too much. Which results in a waste of resources and generates no economic benefits at all. It will not affect digital mobile e-learning, but not the main determinant. The technical teacher ratio is supported and the sign is consistent with Ozdamli & Cavus (2011).

(5) Total equipment expenses associated with tablet PC (Z_5)

Based on the estimated results shown in Table 9. The effect (β_5=5.4×10^{-7}***) of total equipment expenses associated with tablet PC on school's cross-efficiency model efficiency in the model has the significant 5% level and positive relationship. The government is pursuing a comprehensive and new learns model strategy. That is, to be where the students able to experience the authentic joy of new learning model and attract students join. Thus, it is necessary for the Government to adopt some measures, such as skills training (such as training personel), capital support (such as budget), and so on, to assist the school in upgrading the Wi-Fi is a technology and network equipment. If it is the internet and network equipment or device needs to be constructed well and completely. The new learns model will steadily grow in importance over the longer term. Our empirical results indicate that the total equipment expenses associated with tablet PC have a positive effect on the school management efficiency due to the increasing costs for furnishing the related internet. Thus, it will affect digital mobile e-learning and the main determinant. The result of total equipment expenses is supported and the sign is consistent with Ozdamli & Cavus (2011).

(6) School location (Z_6)

The effect of school location (β_6= 0.081***) on school's cross-efficiency model efficiency in the model is significant 5% level and positive relationship as indicated in Table 9. Hence, the effect of school location on school's cross-efficiency is significant. For many years, high schools in various counties and cities in Taiwan have gradually and almost introduced education reforms and innovative teaching through mobile digital e-learning. The government gives the modern metropolis of focus supported by priorities Implementation that especially in the principal urban centers (such as Taipei city).Hence, the principal urban centers have the capacity to provide more funding for the support of teaching equipment, start building a whole new learning environment for the students. Further, to provide innovative digital mobile e-learning technology solutions covering with them to achieve a more effective digital mobile e-learning education. This may be also one of the reasons that the effect of school location on school's cross-efficiency is significant. Thus, the degree of school's cross-efficiency also needs to be taken into account their school location such as equipment, teaching quality, management decisions and etc. (Liu *et al.,* 2016).

goodness-of-fit of the estimated model

Based on statistical analysis, the empirical results are good fit with log likelihood 51.96 in model, Wald test statistic 14.27*** in model. Durbin Watson Test statistic equal 1.913, White statistic 8.005 and ARCH Test 4.03 in model respectively (Table 9). Both show neither autocorrelation nor heteroscedasticity in estimated error term. This information also indicates that our discussions above on these determinants affecting operational efficiencies of the high schools in this study would be more accurate and appropriate.

5. Concluding remarks

In this study, we firstly applycross efficiency model to analyze the cross-efficiency model of high school in Taiwan and then justify whether mobile digital learning can affect a school's cross-efficiency model factors by Truncated Bootstrapped Regression (TBR).

Based on our empirical results from DEA method, Since the introduction of digital mobile e-learning in 2012, there have three schools reached an overall technology efficiency rate of "1" for three years in a row, respectively the Taipei First Girls' High School, Taipei Municipal Fuxing Senior High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School etc.

On the other hand, the remaining five schools failed to reach the efficiency rate of "1".

We have presented the DEA Cross-Efficiency model to improve the DEA mode shortcomings. The results show a new rank all DMUs, these nine schools departments is rank as

$DMU_3 > DMU_1 > DMU_2 > DMU_6 > DMU_7 > DMU_8 > DMU_4 > DMU_9 > DMU_5$.

Thus, the results show the DEA Cross-Efficiency model ready to improve the DEA mode shortcomings, give a new rank all DMUs. Our result is consistent with Sexton *et al.,* (1986) justified.

In this study, we also apply the TBR to find that the school size, tablet PC numbers, total equipment expenses associated with tablet PC and school location are important determinants for affecting efficiency of school management. Owing to the government is full implementation of the new learns model, that is, to be where the students able to experience the authentic joy of new learning model and attract students join. Thus, the digital mobile e-learning is a new model, the teachers of today have to learn new teaching techniques to master the activity approach, and also up-to-date teaching model aids, and continued to much other innovation in class. Our empirical results further demonstrate and justify that school location and school public-private attribute are to affect the efficiency of school management.

The result of the study suggested that in order to increase the school's cross-efficiency model efficiency. The first assist the school in upgrading the Wi-Fi technology and network equipment. In general, the school adds to the Wi-Fi technology and network equipment. That would enlarge the school network and as to attract more school will adopt the new learning. It is where the students able to experience the authentic joy of new learning model and attract students join. Thus, the schools will increase school size. However, it should be noted that total equipment expenses associated with tablet PC have the negative influence on school management efficiency due to the increasing costs for furnishing the related internet and network equipment or device to facilitate for teaching and learning among teachers and students by digital mobile e-learning. The results of this research can also be the reference for educational authorities when formulating policies and regulations for promoting digital mobile e-learning in high school in Taiwan.

Lastly, the conclusions and recommendations presented here are based on the models constructed, sample data collected, and research methodologies employed for this study. Hence, it is necessary to take into consideration the current situation and changes in the environment that are impacting the public and private high schools and vocational schools in the Taiwan District, so any application of our findings can be further tailored to yield more accurate conclusions.

References

Banker, R.D., Charnes, A., & Cooper, W.W. (1984). Some models for the estimation of technical and scale inefficiencies in data envelopment analysis. *Management Science,* 30(9), 1078–1092. 10.1287/mnsc.30.9.1078

Badri, M. A., & Mourad, T. (2012). *Determinants of School Efficiencies in Abu Dhabi Using DEA*. In International Conference on Management and Education Innovation IPEDR (37).

Celen, A. (2013). Efficiency and productivity (TFP) of the Turkish electricity distribution companies: An application of two-stage analysis. *Energy Policy*, 63, 300-310. doi. 10.1016/j.enpol.2013.09.034

Charnes, A., Cooper, W.W., Lewin, A.Y., & Seiford, L.M. (1994). Introduction. In *Data Envelopment Analysis: Theory, Methodology, and Applications*, (pp.3-21). Springer Netherlands.

Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research,* 2(6), 429–444. doi. 10.1016/0377-2217(78)90138-8

Crescente, M. L., & Lee, D. (2011). Critical issues of m-learning: design models, adoption processes, and future trends. *Journal of the Chinese Institute of Industrial Engineers*, 28(2), 111-123. doi. 10.1080/10170669.2010.548856

Chen, W., Zhou, K., & Yang, S. (2017). Evaluation of China's electric energy efficiency under environmental constraints: A DEA cross efficiency model based on game relationship. *Journal of Cleaner Production,* 164, 38-44. doi. 10.1016/j.jclepro.2017.06.178

Dawabi, P., Wessner, M., & Neuhold, E. (2004). Using mobile devices for the classroom of the future. Learning with mobile devices research and development. Attawell, J. & Savill-Smith C. (Ed), pp.55-59.

Du, J., Cook, W.D., Liang, L., & Zhu, J., (2014). Fixed cost and resource allocation based on DEA cross efficiency. *European Journal of Operational Research*, 235(1), 206-214. doi. 10.1016/j.ejor.2013.10.002

Doyle, J., & Green, R. (1994). Efficiency and cross-efficiency in DEA: Derivations, meanings and the uses. *Journal of the Operational Research Society*, 45(5), 567–578. doi. 10.1057/jors.1994.84

Falagario, M., Sciancalepore, F., Costantino, N., & Pietroforte, R. (2012). Using a DEA-cross efficiency approach in public procurement tenders. *European Journal of Operational Research*, 218(2), 523-529. doi. 10.1016/j.ejor.2011.10.031

Farrar, D.E., & Glauber, R.R. (1967). Multicollinearity in regression analysis: The problem revisited, *The Journal of Economics and Statistics*, 49(1), 92-107. doi. 10.2307/1937887

Goh, T., & Kinshuk, D. (2006). Getting ready for mobile learning—adaptation perspective. *Journal of Educational Multimedia and Hypermedia*, 15(2), 175-198.

Hausman, J. (1978). Specification tests in econometrics, Econometrics, 46(6), 1251-1271. doi. 10.2307/1913827

Kumbhakar, S.C., & Lovell, C.A.K. (2000). *Stochastic Frontier Analysis*, Chambridge University Press.

Liu, H.H., Kuo, F.H., & Li, L.H. (2016). The operating efficiency of vocational and senior high schools in Xindian district of New Taipei City: Three envelopment models in DEA. *International Business Research*, 9(11), 116-125. doi. 10.5539/ibr.v9n11p116

Milrad, M., Hoppe, U., Gottdenker, J., & Jansen, M. (2004). Exploring the use of mobile devices to facilitate educational interoperability around digitally enhanced experiments. In Wireless and Mobile Technologies in Education, 2004. Proceedings. The 2nd IEEE International Workshop on (pp.182-186).

Ozdamli, F., & Cavus, N. (2011). Basic elements and characteristics of mobile learning. *Procedia-Social and Behavioral Sciences*, 28, 937-942. doi. 10.1016/j.sbspro.2011.11.173

O'Malley, C., Vavoula, G., Glew, J.P., Taylor, J., Sharples, M., Lefrere, P., ... & Waycott, J. (2005). Guidelines for learning/teaching/tutoring in a mobile environment. [Retrieved from].

Oral, M., Amin, G.R., & Oukil, A., (2015). Cross-efficiency in DEA: A maximum resonated appreciative model. *Measurement,* 63, 159-167. doi. 10.1016/j.measurement.2014.12.006

Sexton, T.R., Silkman, R.H., & Hogan, A. J. (1986). Data envelopment analysis: Critique and extensions. In R.H. Silk (Ed.). *Measuring Efficiency: An Assessment of Data Envelopment Analysis*, (32), pp. 73–105). San Francisco: Jossey-Bass.

Sexton, T.R., Leiken, A.M., Sleeper, S., & Coburn, A.F. (1989). The impact of prospective reimbursement on nursing home efficiency. *Medical Care*, 154-163.

Simar, L., & Wilson, P. (2007). Estimation and inference in two-stage, semi-parametric models of production processesi *Journal of Econometrics*, 136(1), 31-64. doi. 10.1016/j.jeconom.2005.07.009

Singh, M. (2010). M-Learning: A new approach to learn better. *International Journal of Education and Allied Sciences,* 2(2), 65-72.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrical*: *Journal of the Econometric Society*, 26(1), 24-36. doi. 10.2307/1907382

Wang, Y.S., Wu, M.C., & Wang, H.Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology*, 40(1), 92-118. doi. 10.1111/j.1467-8535.2007.00809.x

Wu, J., Sun, J., & Liang, L., (2012). Cross efficiency evaluation method based on weight-balanced data envelopment analysis model. *Computers & Industrial Engineering*, 63(2), 513-519. doi. 10.1016/j.cie.2012.04.017

Wu, J., Chu, J., Sun, J., Zhu, Q., & Liang, L., (2016b). Extended secondary goal models for weights selection in DEA cross-efficiency evaluation. *Computers & Industrial Engineering*, 93(C), 143-151. doi. 10.1016/j.cie.2015.12.019