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

Upgrading school efficiencies and learning interests through innovative teaching of digital mobile e-learning

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Abstract. Assessing the digital mobile e-learning whether to affect school efficiency is an important yet complex issue. Consequently, this study goal of this research is to evaluate the innovative teaching to affect school efficiency (total efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) estimated by the data envelopment analysis (DEA) through using digital mobile e-learning of high school in Taiwan. Additionally, the Tobit regression model (TRM) is employed to discuss whether the other determinants affect using digital mobile e-learning of school efficiency. The findings can briefly be concluded as follows. 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) technical Efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) in the TRM analysis, it also indicates that school size, teacher-student ratio, school high-vocational attribute, especially the numbers of technical teachers in teaching or consulting about digital mobile e-learning knowledge and numbers of Tablet PC (the proxy for digital mobile e-learning) an important role in affecting these three efficiency of school management. Besides, the results show of total equipment expenses associated with tablet PC has a small negative influence on school management efficiency. Due to increasing costs for network equipment small effects on teaching and learning among teachers and students. The results of this research can also be the reference for educational authorities when formulating policies and regulations for promoting digital mobile e-learning.
Keywords. Technical efficiency, Pure technical efficiency, Scale efficiency, Digital mobile e-Learning, Data envelopment analysis (DEA), Tobit regression model (TRM),Vocational and senior high school.
JEL. I21, I25, I28.

1. Introduction

Early Mobile learning (m-learning) is considered to be the simplification of learning and access to educational content through the use of mobile devices, technology was incorporated into teaching merely as a supplemental tool. In recent years, the fast advancement of information technology and continuous improvement of mobile digital learning (such as smart phones, PDAs, and tablets) have contributed to a steady growth of software and hardware development for digital learning technology. Now the digital learning environments are created to support these advances in order to make learning more flexible and engaging, potentially by anyone, anytime and anywhere. Moreover, new technology is playing a pivotal role in digital mobile e-learning today and has

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allowed teachers to experience the importance and emerging trend of combining technology with instruction in the classroom. Hence, the Department of Education and the LearnMode Education Foundation in Taiwan have collaborated at the grassroots level to promote the combination of mobile technology and teaching to schools in various counties and cities in Taiwan. The aim is to help teachers and students in these institutions to develop better teaching experience by utilizing wireless networks or platforms like mobile applications, as well as to the school's introduction of new teaching ideas, methods, or devices and increase students' interest in learning by utilizing mobile digital learning.

On the other hand, Taiwan is facing the challenge of a low birth rate which also significantly impacts educational institutes, particularly in terms of how well school management and efficiency. Hence, schools need to change or transform the way in which they operate in order to increase schools' competitiveness. Hence, the Department of Education collaborated with grassroots foundations 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 2014, more than 100 senior high schools to use digital mobile e-learning, in 2015 begin the officially enter to primary school and middle school.

Thereupon 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. Little is digital mobile e-learning has thus become a topic of interest to both the academics and the private sector. Public and private schools alike are striving to highlight their respective strengths and to increase their competitive advantages, meet students' and parents' needs, and establish unique attributes through innovative operations, so schools can win parents' and students' favorable consideration (Chiang, 2009).

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 fairly large body 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 self-leaning capability, and in turn raising schools' operational efficiency. There has thus far been relatively little research. Up to this point, the 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.

The study of Liu & Kuo (2017) assessedoperating Efficiency and its effect from innovative teaching through digital mobile e-learning for public and private high schools. However, they do just consider how innovative teaching through digital mobile e-learning affect only on total efficiency (TE) for public and private high schools. In this study, we further consider whether it alsohas effectson pure technical efficiency (PTE) and scale efficiency (SE) of the school management. Hence, this paper has two aims: first, it investigates the evolution to analyze the operational efficiency of high school in Taiwan sector by estimating three efficiency measures, namely total efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) and then attempts to find digital mobile e-learning and other main determinants on these three efficiency measures. In order to do so,we firstly using the Data Envelopment Analysis (DEA) non-parametric methodology analyze the operational efficiencies (TE, PTE and SE) of high schools in this study and justify whether mobile digital learning can still affect a school's TE, PTE and SEby Tobin regression model (TRM).

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. Review of literature

Recent technological advancements have altered modern life and learning. Aided by information technology, learning has transcended the limit of time and space. The advantage of digital mobile e-learning lies in the design of both mobile devices and mobile learning environments, which differ from those common in traditional e-learning. For example, the traditional e-learning teaching model, which is primarily dependent on hardwired networking technologies, has evolved to a model based on wireless networking and mobile devices (Liu & Hwang, 2009). Moreover, the devices used in mobile e-learning are capable of supporting interactions between different learners and learning environments. Network-based technologies have pushed beyond traditional unidirectional learning, and have enabled interactive learning. With the aid of mobile technologies, learners can now access information and enjoy learning anytime and anyplace (Chen & Lin, 2007; Liu & Chen, 2009; Luo & Hsu, 2009).

On the other hand, Research indicates that the characteristics of mobile learning should be organized, and the way they are applied to mobile learning activities and the application methods and the duration of the application time should be planned well in advance. These reasons have learner, teacher, environment, content and assessment are basic elements of the complete mobile learning. The core characteristics of mobile learning are ubiquitous, portable size of mobile tools, blended, private, interactive, collaborative, and instant information. They enable learners to be in the right place at the right time, that is, to be where they are able to experience the authentic joy of learning (Badri & El, 2012; Ozdamli & Cavus, 2011; Dickerson & Browning, 2009).

The above discussion suggests that digital mobile e-learning is a new model of learning and 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. Moreover, that has gained considerable interest among industrial, governmental, and academic sectors. In subsequent years numerous studies were carried out on the effectiveness of digital mobile e-learning to increase learning motivation among students. For example, Hwang & Wu (2014) point out in their literature review that among the seven renowned Social Sciences Citation Index (SSCI) databases on e-learning, approximately 214 studies published between 2008 and 2012 were related to digital mobile e-learning. Most of these studies indicate that the introduction of mobile e-teaching can indeed increase learning motivation among students. IN recent years, many scholars have employed Data Envelopment Analysis (DEA) to analyze the operational efficiency and examine whether the widespread utilization of assessments can effectively enhance growth efficiency in order to improve operations management. According to the statistics, DEA has been applied empirically to more than one thousand cases in fields as diverse as transportation, educational administration, law, forest management, medicine, banking, military maintenance, and administration. Due to an abundance of prior research, the present study only reviewed relevant Taiwanese literature, which revealed that most studies focused on evaluating the operational performance of universities, high schools, middle schools, vocational schools, and national elementary schools (Wang *et al.,* 1991; Chen, 1998; Gu, 1999; Liu, 2000; Hwang, 2001; Li, 2009; Hwang, 2012).

DEA was developed by Charnes *et al.* (1978) to evaluate public sector and not-for-profit organizations. It can deal with multiple inputs and outputs for measuring the performance of each DMU. Hence, it can calculate anaggregate performance measure based on a ratio of outputs and inputs.Our literature review revealed that many studies report on using DEA to measure performance of schools (Coelho *et al.,* 2008; Mayston, 2003; Dyson, 2000). Up to this point, DEA 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).

As mentioned above, the education reforms coupled with innovative teaching which incorporates digital mobile e-learning can indeed increase students' interest in learning and their motivations. On the whole has been relatively little progress 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 and whether there are any differences in operational efficiency between county schools and city schools. There has thus far been relatively little research the area. On the other hand, scanty theoretical discourses on topics such as whether the school that introduces digital mobile e-learning can increase the school's competitiveness and operational efficiency. Common sense seems to indicate its importance, but we lack empirical support. 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 self-strengthening initiatives.

3. Research methodology

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 a DEA approach because our goal was to unravel efficiencies of school management using a unique efficiency index. DEA has the significant advantage of not imposing a particular functional form on the liaison between inputs and outputs when making between-schools comparisons, as compared to parametric methods (Thieme *et al.,* 2013). Further, this study uses TRM to analyze that factors affecting the relative efficiencies of schools in various counties and cities by utilizing related factors as explanatory variables.

3.1. Study model

3.1.1. 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):

$$\text{Max } h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \quad (1) \quad s.t \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad , \quad j = 1,\dots,n$$

$$u_r, v_i \ge \varepsilon > 0, \quad r = 1,\dots\dots,s, \quad i = 1,\dots\dots,m \qquad (1)$$

where x_{ij} is the amount of the i-th input to DMU j, y_{rj} is the amount of the r-th output to DMU j; u_r , v_i are called r virtual multiplier output and i virtual input multiplier; The value of h_k obtained 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 (SC).

3.1.2. Tobit regression model（TRM）

The first stage includes the estimation of three measures of efficiency (Technical Efficiency, Pure Technical Efficiency and Scale Efficiency) by applying the non-parametric Data Envelopment Analysis (DEA) methodology. As the efficiency rate derived from DEA is often the function of influential variables such as DMU characteristics, region, attributeand 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 Tobit regression model belongs tothe 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 (2) forthat 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:

$$y_i = \begin{cases} y^*_{i=\beta x_i + u_i} & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \tag{2}$$
$$u_i \sim \text{IN}\ (0, \sigma^2)$$

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 ofthree measures of efficiency (TE, PTE and SE). 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 employTobit regression analysis to examine the effects of explanatory variables includingdigital mobile e-learning factors.

4. Empirical results and analysis

The empirical analysis of this study mainly comprised two parts: firstly, this section will adopt the DEA modelto analyze the relative three efficiencies of schools(TE, PTE and SE)analysis method. Followed by the application of the DEA model and Furthermore, this study appliesTobin regression model to analyze the factors which include digital mobile e-learning factors that affecting the relative efficiencies of schools (TE, PTE and SE) in various counties and cities in Taiwan.

4.1. Results of efficiency analysis for DEA mode

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, Section3 analyzes the efficiency analysis of DEA mode.

4.1.1. Study objects and variablefor inputs and outputs in this study

The study objects and variable selection for inputs and outputs in this study are described as follows:

A. Study objects

This study aimed to analyze if the introduction of digital mobile e-learning increases schools' operational efficiency and if there are any differences in students' learning effectiveness in school between counties and cities. The study spanned four years and included periods before and after the introduction of digital mobile e-learning as well as periods during which such introduction continued. The names, attributes, and locations (county or city) of the above schools (study objects) are outlined in Table 1.

Table 1. *School names and characteristic*

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

B. Variables selection for inputs and outputs in this study

The input and output variables for the above schools that introduced digital mobile e-learning and teaching are described as follows. Input variables included four items: the number of subjects and sessions, the number of teachers, the number of part-time teachers, and the number of faculty and staff. Output variables included three items: the total population of the school, the number of graduates, and the number of graduating classes. The selection of input and output variables was also predicated on the fact that DEA is a good methodology for evaluating efficiency. The study also formulated basic hypotheses for the model. If the conditions studied failed to match the hypotheses, the utility of the model would be compromised. Hence, when applying DEA, the number of Decision Making Units (DMUs) should be equal or greater than the multiplication of the number of inputs with the number of outputs. Otherwise, the efficiency estimated for each DMU through DEA would approximate the value of 1 and fail to discriminate among DMUs (Cooper *et al.,* 2007). As this study adhered to this principle, operational efficiencies could be estimated and compared between schools that introduced digital mobile e-learning and those that did not.

In this paper, the input-output variables definitions of public and private vocational schools in the four cities, Taiwan are listed in Table 2 and Table 3. The including five input variables: academic department, number of full-time teachers, number of part-time teachers, and staff. There are three output variables: number of students, graduates student and classes.

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

4.1.2. 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.

A. Data descriptions

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

Table 4. *Descriptive statistics*

	Minimum	Maximum	Mean	SD	variance
academic department	1.00	3.00	1.78	0.93	0.87
number of full-time teachers	70.00	195.00	143.11	38.97	1518.64
number of part-time teachers	1.00	73.00	17.70	19.62	385.06
staff	17.00	80.00	30.59	16.87	284.64
number of school students	723.00	4729.00	1962.33	1115.21	1243700.77
graduate student	294.00	1146.00	598.96	274.68	75447.96
classes	18.00	109.00	53.19	25.77	664.00

B. 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.

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

Finally, 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 chosen were the total population of the school, the number of graduates, and the number of graduating classes. The results of final correlation analysis are displayed in Table 5.

4.1.3. Efficiency analysis

Regarding efficiency analysis, Section 1 analyzes total efficiency, Section 2 indicates pure technical efficiency and Section 3describes scale efficiency.

A. Technical (total) efficiency (TE)

As shown in Table 6 below after imported digital mobile e-learning. Since the introduction of digital mobile e-learning in 2012, only four out of the nine schools in four counties and cities reached an overall technology efficiency rate of “1” for three years in a row, including the Taipei First Girls’ High School, Taipei Municipal Fuxing Senior High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School. 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	1	1	1	1
2	1	1	1	1	1
3	0.838	0.848	0.796	0.827	8
4	1	1	0.955	0.985	5
5	1	1	1	1	1
6	1	0.784	0.758	0.847	7
7	1	1	0.797	0.932	6
8	0.578	0.637	0.985	0.733	9
9	1	1	1	1	1

B. Pure technical efficiency (PTE)

As shown by the data in Table 7 on pure technical efficiency, the efficiency rates of five out of the nine schools in four counties and cities that introduced digital learning for three years in a row reached “1”, including the Taipei First Girls’ High School, Taipei Municipal Fuxing Senior High School, Chi Jen High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School. All these schools are located in Taipei City or New Taipei City. This result shows that these schools utilized their resources effectively and did not need to make any further adjustment or improvement, when external factors were excluded. On the other hand, the efficiency rates of the remaining four schools were below “1”, including the National Hualien Industrial Vocational High School, National Lo-Tong Senior High School, National Yang Ming Senor High School, and Taipei Municipal Zhong-Lun High School. These schools all needed to make further improvement or adjustment, when external factors were excluded. This result shows that differentials in resources do exist across counties and cities, which could impact the pure technical efficiency of schools. This explains why the efficiency rates of some schools are lower than “1," that is, because of the county or city where they are located.

C. Scale efficiency (SE)

As shown by the results in Table 8 on scale efficiency, the efficiency rates of four out of the nine schools in four counties and cities that introduced digital learning for three years in a row reached “1”, including the Taipei First Girls’ High School, Taipei Municipal Fuxing Senior High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School. All these schools are located in Taipei City or New Taipei City. On the other hand, the five remaining 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. The Taipei Municipal Zhong-Lun High School was the only school with declining returns to scale. Hence, in order to optimize its scale of operation, the school needs to reduce its scale. Too many resources may have rendered the school's operation inefficient. With increasing returns to scale, the other schools need to expand their scales of operation in order to reach the optimal scale efficiency. They have not received sufficient resources, which also renders schools' operations inefficient.

Table 7. *Pure technical efficiency analysis high schools in this study*

DMU	2013	2014	2015	Average	Ranking
1	1	1	1	1	1
2	1	1	1	1	1
3	0.850	0.856	0.826	0.845	9
4	1	1	1	1	1
5	1	1	1	1	1
6	1	0.917	0.869	0.929	7
7	1	1	0.956	0.985	6
8	0.761	0.774	1	0.845	8
9	1	1	1	1	1

Table 8. *Scale efficiency analysis of high schools*

DMU	2013	2014	2015	Average	returns to scale (RTS)	Ranking
1	1	1	1	1	Constant	1
2	1	1	1	1	Constant	1
3	0.987	0.991	0.963	0.980	Increasing	9
4	1	1	0.954	0.985	Increasing	1
5	1	1	1	1	Constant	1
6	1	0.855	0.871	0.909	Increasing	7
7	1	1	0.833	0.944	Increasing	6
8	0.760	0.823	0.985	0.856	Decreasing	8
9	1	1	1	1	Constant	1

4.2. Results of tobit regression model (TRM)- explaining the determinants affecting school efficiency

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

The reason for we used Tobit regression application is that when the dependent variable is continuous but constrained by something, the Tobit regression model assumes truncated normal distribution in place of normal distribution and employs the maximum likelihood estimation (MLE) method. Since the DEA scores have lower and upper limits, estimation with OLS would lead to bias results for the efficiency parameter since it assumes normality and a homoscedastic distribution of the error term (Jackson & Fethi, 2000). There may be a truncated bias in the OLS regression model. This is why we used the Tobit regression model (Tobin, 1958) with MLE rather than the OLS estimation.

Based on the related theories and literature provided useful information in this study, it is indicates that the variables usually be used related researches, and we focus the major variables that relate to the determinants of mobile digital e-learning. Basic model setups can be described as follows:

A. Model setups

Basic model setups can be described as following Equation (4), (5), and (6):

$$TE_{it} = f(Z_{1it}, Z_{2it}, Z_{3it}, Z_{4it}, xZ_{5it}, Z_{6it}, Z_{7it}, Z_{8it}) \quad (4)$$
$$PTE_{it} = f(Z_{1it}, Z_{2it}, Z_{3it}, Z_{4it}, xZ_{5it}, Z_{6it}, Z_{7it}, Z_{8it}) \quad (5)$$
$$SE_{it} = f(Z_{1it}, Z_{2it}, Z_{3it}, Z_{4it}, xZ_{5it}, Z_{6it}, Z_{7it}, Z_{8it}) \quad (6)$$

The statistical model can be written as follows (Equation 7):

$$EFF_{it} = \beta_0 + \beta_1 Z_{1_{it}} + \beta_2 Z_{2_{it}} + \beta_3 Z_{3_{it}} + \beta_4 Z_{4_{it}} + \beta_5 Z_{5_{it}} + \beta_6 Z_{6_{it}} + \beta_7 Z_{7_{it}} + \beta_8 Z_{8_{it}} + \varepsilon_{it} \quad (7)$$

The theoretically expected signs of the coefficients are:

$\beta_1>0, \beta_2>0, \beta_3>0, \beta_4>0, \beta_5>0, \beta_6>0, \beta_7>0, \beta_8>; i=1\ldots9; t=1\ldots n$

Where

EFF_{it} : The efficiency score (either TE, PTE or SE) of School i during the period 2013 to 2015

$Z_{1_{it}}$: School size (total numbers of school students) of School i

$Z_{2_{it}}$: Teacher-student ratio (average number of students per teacher members) of School i

$Z_{3_{it}}$: The total number of tablet PC of School i

$Z_{4_{it}}$: 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

$Z_{5_{it}}$: Total equipment expenses associated withtablet PCof School i

$Z_{6_{it}}$: Schoollocation dummy: in the northern area:1, other areas: 0

$Z_{7_{it}}$: School public–private attributedummy: public high schools:1, private high schools: 0

$Z_{8_{it}}$: School high-vocational attribute dummy: senior High School: 1, vocational high schools: 0

ε_{it}: Disturbance terms, $\varepsilon_{it} \sim$iid N $(0,\sigma^2)$

A. Tobit regression results: Explaining the determinants affecting school efficiency

In this study, we use panel data (time series and cross-section data) to estimate how each factor includingdigital mobile e-learning affecting operational 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. The Hausman specification test compares the fixed versus random effects under the null hypothesis that the individual effects are uncorrelated with the other repressors in the model (Hausman, 1978). Prior the estimation for Equations (5), the Hausman test (p value= 0.0041, 0.0024) shows that the p value is less than 0.05 which is significant. This implies that the null hypothesis that random effect model which consistent and efficient is rejected. 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 school's operational efficiency of three efficiencies, namely the operational efficiency (TE, PTE and SE).

Table 9. *The determinants affecting on school efficiency*

Variable		TE	t-value	PTE	t-value	SE	t-value
Constant	β_0	-7.790***	-7.290	-1.637***	-1.954	-5.517***	-9.995
$\boldsymbol{Z_1}$	β_1	2.176***	8.682	0.714***	3.389	1.551***	12.914
$\boldsymbol{Z_2}$	β_2	-0.450***	-9.559	-0.178***	-3.986	-0.290***	-15.326
$\boldsymbol{Z_3}$	β_3	0.038***	8.904	0.015***	3.853	0.024***	13.754
$\boldsymbol{Z_4}$	β_4	0.002***	5.540	0.001***	4.170	0.001***	5.268
$\boldsymbol{Z_5}$	β_5	$-3.650\times10^{-5***}$	-8.891	$-1.500\times10^{-5***}$	-3.846	$-2.300\times10^{-5***}$	-13.676

Z_6	β_6	-0.047	-1.572	-0.061	2.924	-0.1113	-7.302
Z_7	β_7	0.038	1.851	0.003	0.171	0.037***	3.607
Z_8	β_8	0.073***	3.000	0.039***	2.350	0.038***	3.091
Likelihood		39.82**		55.69**		60.62**	
Wald Test		6.12**		4.024*		23.30***	
Durbin Watson		1.927		1.855		1.96	
White Test		11.61		12.27		10.63	
ARCH Test		0.15		0.02		0.384	

Notes: **, ***, denotes statistical significance at the 5%, 1%, respectively.

As indicated in Table 9, we can find firstly that school size (β_1) in TE, PTE and SE, teacher-student ratio (β_2) in TE, PTE and SE, tablet PC numbers (β_3) in TE, PTE and SE, technical teacher ratio (β_4) in TE, PTE and SE, the total equipment expenses associated with tablet PC (β_5) in TE, PTE and SE, school public–private attribute (β_7) and school high-vocational attribute (β_8) are important determinants for affecting efficiency of school management.

The analysis was conducted using Tobit Regression Results model and we used different focus the major variables depending on the variable. Hence, the results are as follows:

(1) School size (Z_1)

According to the empirical results shown in Table 9, the effects of school sizeon three school's operational efficiencies (β_1=2.176 in TE, β_1=0.714 in PTE, β_1=1.551 in SE) are significant at 1% level and positive relationship as we expected but their effects have somehow different. The school size has more effects on TE. The results show that it implies that the larger the school, the economics of scale can be accomplished when outputs expand (such as teaching functions, research functions, and education or employment opportunities (enrollment rates)) and then cause school's operational efficiency. Overall, this relationship of three efficiencies is significant and in line with previous studies. This result is consistent with Dickerson & Browning (2009) justified that a successful digital mobile e-learning integration, increasing more persons such as school students to apply this digital mobile e-learning is important. Thus, an increase in the number of school students may also add to the school's operational efficiency (TE, PTE and SE).

(2) Teacher-student ratio (Z_2)

Based on empirical results shown in Table 9. The effect of the teacher-student ratioin t hree efficiencies (β_2=-0.450 in TE, β_2=-0.178 in PTE, β_2=-0.290 in SE)on school's operational efficiency (TE, PTE and SE) is significant 1% level and negative value. One of the main reasons that the low fertility problem in Taiwan, the number of students (output variable) decreased and overestimate the teacher-student ratio. i.e., due to the number of students is reduced and leads to too many teachers as input in each school. Overall, this relationship of three efficiencies is significant and in line with previous studies. This result is consistent with the Previous research of Badri & El (2012) supports our findings. Therefore, resource misallocation in teachers and students and the cost per teacher over counts and hence reduce the school's operational efficiency (TE, PTE and SE).

(3) Tablet PC numbers (Z_3)

As can be seenthat the results shown in Table 9. The effect of tablet PC numbers in three efficiencies (β_3=0.038 in TE, β_3=0.015 in PTE, β_3=0.024 in SE)on school's operational efficiency (TE, PTE and SE) in the model have significant at 1% level and positive relationship as we expected. The results show that the innovative teaching to affect school efficiency through using digital mobile e-learning by Tablet PC enable learners to be in the right place at the right time, that is, to be where they are able to experience the authentic joy of learning and attract students join to learning. As results, the more Tablet PC numbers to be applied in high school will cause the school's operational efficiency. Overall, this relationship of three efficiencies is significant and in line with Ozdamli & Cavus

(2011) justified that a successfully attract students to join digital mobile e-learning and then add to the school's operational efficiency.

(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 of the numbers of technicians as consultants for teaching tablet PC knowledge total number of teachers in school) in three efficiencies (β_4=0.002 in TE, β_4=0.001 in PTE, β_4=0.001 in SE) on school's operational efficiency (TE, PTE and SE) in the model have significant at 1% level and positive relationship as we expected. The transition of the media formats changed the role of the average teacher from being an expert towards being a presenter of the expertise of others. 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. Thus, an increase in the technical teacher ratio may also add to the, even more, school students to apply for this digital mobile e-learning program.The results show that 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 operational efficiency. Overall, this relationship of three efficiencies is significant and in line with Ozdamli & Cavus (2011) also supports our analysis that a successful digital mobile e-learning integration, to induce increasing more persons learn such as school students to apply this digital mobile e-learning and then add to the school's operational efficiency.

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

Based on the estimated results shown in Table 9. In three efficiencies (β_5=-3.650×10^{-5} *** in TE, β_5=-1.500×10^{-5} *** in PTE, β_5=-2.300×10^{-5} *** in SE) of total equipment expenses associated with tablet PC on school's operational efficiency in the model has significant at the 1 % level and negative relationship.In general, Mobile Learning is a type of e-learning, in distance or face to face, which uses mobile technology; it's designed to respond appropriately to the mobility of students and their modern preferences (Droui *et al.,* 2013). Mobile learning is seen asthe natural evolution of e-learning. M-learning is eLearning through a mobile device and a wireless transmission. Furthermore, mobile e- learning (mobile-e-learning) as a kind of learning model allowing learners to obtain learning materials anywhere and anytime. Overall, this relationship of three efficiencies is significant and in line with Ozdamli & Cavus (2011), the characteristics of mobile learning should be organized, and the way they are applied to mobile learning activities and the application methods and the duration of the application time should be planned well in advance. The internet and network equipment or device needs to be constructed well and completely. Our empirical results indicate that the total equipment expenses associated with tablet PC have a negative influence on school management efficiency. For the school that a successfully attract students to join digital mobile e-learning. Thus the increasing costs for furnishing the related internet and network equipment or device to facilitate 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.

(6) School location (Z_6)

The effect of school location in three efficiencies (β_6=-0.047 in TE, β_6=-0.061in PTE, β_6=-0.113 in SE) on school's operational efficiency (TE, PTE and SE)in the model has non-significant shown in Table 9. As a matter of fact, the reason is that the study examples of our case study are quite smaller. Hence, the effect of school location on school's operational efficiency may not significant. In this study, on the other hand, 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. By 2014, more than 100 senior high schools to use digital mobile e-learning, in 2015 begin the officially enter to primary school and middle school. This may be also one of the reasons that the effect of school location on school's operational efficiency may not be significant. Mainly, the degree of school's operational efficiency also needs to be taken into account their school attributes such as equipment, teaching quality, management decisions and etc. (Liu *et al.,* 2016).

(7) School public–private attribute (Z_7)

The effect of school public–private attribute (β_7=0.038 in TE and β_7=0.003 in PTE) on school's operational efficiency (which is considered by total efficiency (TE) and which is considered by pure technical efficiency (PTE)) in this study is not significant but positive relationship as indicated in Table 9. Another the effect of school Public–Private attribute (β_7=0.037 in SE) on school's operational efficiency in this study have significant level at 1% and positive relationship as indicated in Table 9. In this study, we consider whether the public or private school has different operational efficiency. Our empirical results depict the effect of school public–private attribute on relationship of TE and PTE efficiencies is non-significant; however, on the SE efficiencies is significant. The reason is Total Efficiency (TE) = Pure Technical Efficiency (PTE) × Scale Efficiency (SC). In fact, the public school accessory equipment comes from the budget of the central government, but the private school accessory equipment of budget comes from oneself school; in other words, when the more the number of students, the school accessory equipment more subsidy. Clearly, teaching quality in public high school, for example, easier applies mobile e-learning environments which utilize the latest technologies to bring an interactive learning environment into learning and teaching activities. ,

(8) School high-vocational attribute (Z_8)

The effect of school high-vocationalattribute (β_8=0.073 in TE, β_8=0.003 in PTE, β_8=0.038 in SE) on school's operational efficiency (TE, PTE and SE) in this study have significant level at 1% and positive relationship as indicated in Table 9. In this study, we consider whether the high or vocational school has different operational efficiency. Our empirical results depict that operational efficiency of high school is better than that of vocational school on the school equipment aspect. The high school accessory equipment mostly comes from the budget of the central government, but the vocational school accessory equipment of budget comes from oneself school. Teaching quality in public high school, for example, easier applies mobile e-learning environments which utilizes the latest technologies to bring an interactive learning environment into learning and teaching activities. This may also cause the high school to have better school's operational efficiency (Liu *et al.,* 2016).

C. Goodness-of-fit of the estimated model

In this study, we use Tobit regression application to explore the determinants of factors that affecting the relative efficiencies of schools (TE, PTE and SE) in various counties and cities in Taiwan. To address this issue, test the model of goodness-of-fit analyses were conducted. Based on statistical analysis, the empirical results are the good fit with log likelihood 39.82, 55.69, 60.62 in model TE, PTE and SE, Wald test statistic 6.12**, 4.024*, 23.30**in model TE, PTE and SE. Durbin Watson Test statistic equal 1.927, 1.855, 1.96, White statistic 9.08 and ARCH Test 0.15, 002, 0.384 in model TE, PTE and SE respectively (Table 9). The results revealed that 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 it investigates apply data envelopment analysis (DEA) to analyze the operational efficiency of high school in Taiwan sector by estimating three efficiency estimators, namely Technical Efficiency (TE), Pure Technical Efficiency (PTE) and Scale Efficiency (SE). Moreover, three efficiencies by Tobin regression model (TRM) for then justify whether mobile digital learning can affect a school's operational efficiency.

Based on our empirical results from DEA method, only four out of the nine schools in four counties and cities reached an overall technical efficiency (TE) rate of "1" for three years in a row, including the Taipei First Girls' High School, Taipei Municipal Fuxing Senior High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School. On the other hand, the five remaining 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. Regardingto the measurement of pure technical efficiency(PTE), the efficiency rates of five out of the nine schools in four counties and cities that introduced digital learning for three years in a row reached "1", including the Taipei First Girls' High School, Taipei Municipal Fuxing Senior High School, Chi Jen High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School. All these schools are located in Taipei City or New Taipei City. As for the measurement for scale efficiency(SE), the efficiency rates of four out of the nine schools in four counties and cities that introduced digital learning for three years in a row reached "1", including the Taipei First Girls' High School, Taipei Municipal Fuxing Senior High School, Taipei Municipal Lishan Senior High School, and Juang Jing Vocational High School. All these schools are located in Taipei City or New Taipei City

This research, we also apply the Tobit Regression Model (TRM) to find the factors affecting the school's operational efficiency of three efficiencies, namely Technical Efficiency (TE), Pure Technical Efficiency (PTE) and Scale Efficiency (SE). These results show a clear and strong relationship between the school size, teacher-student ratio, tablet PC numbers, technical teacher ratio, the total equipment expenses associated with tablet PC and school high-vocational attribute are important determinants for affecting the efficiency of school management. Our empirical results further demonstrate and justify that School size, especially the numbers of technical teachers in teaching or consulting about digital mobile e-learning knowledge and numbers of Tablet PC (proxy for digital mobile e-learning) to affect the efficiency of school management. In addition, we consider whether the public or private school has different operational efficiency. Our empirical results depict the effect of school public–private attribute on relationship of TE and PTE efficiencies is non-significant; however, on the SE efficiencies is significant. The reason is Total Efficiency (TE) = Pure Technical Efficiency (PTE) × Scale Efficiency (SC). In fact, the public school accessory equipment mostly comes from the budget of the central government, but the private school accessory equipment of budget comes from oneself school; in other words, when the more the number of students, the school accessory equipment more subsidy. In order to increase students learning effectiveness to enhance the school's operational efficiency in this study, it is necessary to first add school size, Tablet PC numbers, and technical teachers. The effect of school high-vocational attribute on school's operational efficiency (TE, PTE and SE) in this study have significant and positive relationship. Besides, the results show of total equipment expenses associated with tablet PC has a small negative influence on school management efficiency. Due to increasing costs for network equipment small effects on teaching and learning among teachers and students. The results of this research can also be the reference for educational authorities when formulating policies and regulations for promoting digital mobile e-learning.

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.

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