Advances in Management & Applied Economics, vol. 9, no. 6, 2019, 111-126
ISSN: 1792-7544 (print version), 1792-7552(online)
Scientific Press International Limited

An Another Approach to Explore the Factors affecting Operational Efficiency of School Management from Innovative Teaching through Digital Mobile e-Learning: DEA and Grey Relation Analysis

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Abstract

Assessing whether digital mobile e-learning affects school efficiency is an important yet complex issue. Consequently, the goal of this research is to evaluate the effect of innovative teaching on school efficiency through a data envelopment analysis (DEA) of digital mobile e-learning in a high school in Taiwan. Additionally, we used the grey relational analysis (GRA) model to find the main influencing factors. The empirical findings can briefly be summarized as follows: (1) Importing digital mobile e-learning can greatly enhance the efficiency of school management. (2) The GRA model found factors affecting the school's operational efficiency in a clear and important relationship between the school size, teacher-student ratio, technical teacher ratio, school location, and school high-vocational attribute, all of which are shown to be important determinants affecting the efficiency of school management. Among these, school size seems to be closely connected to digital mobile e-learning. The results of this research can also serve as a reference for educational authorities when formulating policies and regulations to promote digital mobile e-learning.

Keywords: Technical Efficiency, Digital Mobile e-Learning, Data Envelopment Analysis (DEA), Grey Relational Analysis (GRA), Vocational and Senior High School

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Article Info: *Received:* July 7, 2019. *Revised:* August 20, 2019.
Published online: November 1, 2019.

1. Introduction

Education is a key element in national development and plays an important role in human capital development (Garrett, 2010). Thus, the Ministry of Education has acted to improve IT and its infrastructure, pioneering pedagogical advances through the application of new technology developments in school education on an on-going basis.

The Ministry of Education in Taiwan began to import digital mobile e-learning in 2012. By 2019, over 100 junior and senior schools had used the e-learning model throughout Taiwan. Digital mobile e-learning has thus become a topic of interest to both academics and the private sector. Public and private schools are striving to highlight their respective strengths, to increase their competitive advantages, meet students' and parents' needs, and establish unique attributes through innovative operations so as to gain parents' and students' favorable consideration (Chiang, 2009). Moreover, this new learning/teaching model indeed increases students' interest in studying the required courses and other matters. Hence, the digital mobile e-learning method is an important and emerging trend in classrooms of Taiwan.

We all know that the new learning model of digital mobile e-learning, or the "M-Learning" model, offers modern ways to support the learning process through mobile devices, such as handheld and tablet computers, MP3 players, smartphones, and mobile phones. Thus, the teachers of today must learn new teaching techniques to master activity approaches, up-to-date teaching aids, and many other innovations via digital mobile e-learning. At the same time, digital mobile e-learning offers previously unthinkable possibilities of interaction and access to knowledge virtually anywhere in the world (Felice, 2009; Yanaze, 2006).

Although digital mobile e-learning has existed for several decades, only recently has its surge in mainstream popularity motivated researchers to acknowledge its educational value. However, whether the high schools that have introduced mobile digital learning have in fact enhanced classroom teaching, increased in-classroom learning effectiveness, and attracted student attendance, and in turn raised their operational efficiency remains a topic not yet widely addressed in the literature published domestically. The relevant theoretical foundation is likewise not widely discussed and very little attention has been given specifically to the effects of new learning perspectives on the efficiency of school management. Hence, what prompted the current study was to better understand the actual teaching in the field by analyzing appropriate cases of schools in order to find the main influencing factors that might serve as a basis for suitable policy recommendations for schools' operational efficiency.

Hence, in order to address the above issues, we must examine schools' characteristic problems. First, we analyze whether it really improves the operational efficiency of school management to implement digital mobile e-learning and teaching. The efficiencies of school management are measured by DEA. There is good evidence that the DEA model, one of the most popular approaches in management science, is effective for evaluating the relative efficiency of DMUs. However, the DEA model does not show school characteristics and is unable to validate improvements in school effectiveness. Thus, we apply the concepts of the GRA model with fewer samples to determine school efficiency and school characteristics.

Specifically, we apply the DEA model to compute and analyze the operational efficiencies of schools through innovative teaching via digital mobile e-learning, and then apply the GRA model to explore school characteristics regarding the data on the efficiency factors affecting the operational efficiency of school management through innovative teaching via digital mobile e-learning.

This paper is organized as follows. Section 1 introduces the research background and goal of this research. Section 2 reviews the conceptual framework and the overview of the policy. Section 3 briefly reviews the DEA methodology and the GRA model. Section 4 presents the empirical results. Some conclusions are made in Section 5.

2. Literature Review

We all know that mobile technology is a web-based learning ecosystem integrating several stakeholders with technology and processes. With the popularization and expansion of access to the World Wide Web and greater access to devices to access the Internet, such as smartphones, laptops, tablets, and computers, learning using e-learning practices has expanded rapidly all around the world (Cidral, Oliveira, Di Felice, and Aparicio, 2018). As a result, in recent years increasing notice has been taken of the various types of advanced technologies that have been introduced into education, including wearable technology (Vallurupalli et al., 2013), smart boards (Al-Qirim, 2011; Gursul and Tozmaz, 2010), mobile devices (El-Gayar et al., 2011; Eristi et al., 2011; Williams and Pence, 2011), and smart classrooms (Simsek et al., 2010).

There is no doubt that successful teaching cases abound (i.e., success stories) of digital mobile e-learning. For example, many studies have indicated the importance of using tablets during classroom instruction as a way to facilitate student learning (Banister, 2010; Ifenthaler and Schweinbenz, 2013a, b, 2016). Furthermore, Gikas and Grant (2013) found that the uses of mobile devices with multiple applications allows students to access information, interact with peers and teachers, and collaborate in order to construct knowledge. Thus, these technologies make it possible to join different fields of knowledge and assimilate new techniques (such as Augmented Reality (AR)) into digital mobile e-learning.

Thus, digital mobile e-learning readily improves students' interest and willingness to learn. In fact, digital mobile e-learning has seen practical incorporation into various fields of knowledge. However, few studies have been made of its effects in improving school effectiveness. Furthermore, most of the research in this area is biased towards qualitative research or case studies (Arun and Vrishali, 2016; Wang, Lin, and Tsai, 2017).

On the other hand, we know that the DEA model was developed by Charnes et al. (1978) to evaluate public sector and not-for-profit organizations. It can deal with multiple inputs and outputs to measure the performance of each DMU. In the last decade, many advances have been made in the DEA model. Up to this point, the 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 (Chen, 1998; Gu, 1999; Hwang, 2001; Hwang, 2012; Liu, 2000; Li, 2009; Li and Kuo, 2017; Wang et al., 1991).

However, this model cannot determine the main influencing factors. In fact, there are many multiple attribute decision-making (MADM) problems in our daily life. Unlike single attribute decision-making problem, MADM aims to select the best from the existing “alternatives,” “options,” “policies,” “actions,” or “candidates” by considering multiple “attributes,” “goals,” or “criteria,” which are frequently in conflict with each other (Kuo, Yang, and Huang, 2008). Thus, the Grey System Theory proposed by Deng (1982) has been widely applied to various fields (Lin, Chang, and Chen, 2006) and has been shown to be useful for dealing with poor, incomplete, and uncertain information. What is more, the model is able to find the main influencing factors in such fields as hiring decisions (Olson and Wu, 2006), restoration planning for power distribution systems (Chen, 2005), the inspection of integrated-circuit marking processes (Jiang, Tsai, and Wang, 2002), modeling quality function deployment (Wu, 2002), and the detection of silicon wafer slicing defects (Lin et al., 2006). Thus, there is good evidence that using these methods to better understand students and the settings which they learn in should be effective, and that it is feasible for researchers to investigate a wide variety of education questions and find their main influencing factors using grey system theory.

For the most part, this study will apply the DEA model, which provides efficiency, and use the GRA model to find the main influencing factors. We hope that this study will determine the most important school characteristics related to efficiencies in school management so as to explore future trends and factors affecting the relative efficiencies of schools.

3. Research Methodology

The purpose of this research is to analyze whether the efficiency of school management that implemented digital mobile e-learning and teaching really improved. Hence, in the present study, we opted for a DEA approach because our goal was to unravel the 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-school comparisons, unlike parametric methods (Thieme et al., 2013). Further, this study uses grey system theory to find the main influencing factors of schools in various counties and cities by utilizing the 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):

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

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

$$u_r, v_i \ge \varepsilon > 0, \ldots r = 1, \ldots\ldots\ldots, s, \ldots i = 1, \ldots\ldots\ldots, m$$

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 Original grey incidence model

In terms of grey system theory, it is a new methodology that focuses on the problems involving small samples and poor information. It deals with uncertain systems with partially known information through generating, excavating, and extracting useful information from what is available. The theory focuses on the generation and excavation of the partially known information to materialize the accurate description and understanding of the material world. Grey incidence analysis

provides a new method to analyze systems when conventional methods do not seem appropriate. Grey clustering is developed for classifying observation indices or objects into definable classes using grey incidence matrices or grey haptenization weight functions. Prediction is foretelling the possible future development of societal events, political matters, economic ups and downs, so on, using scientific methods and techniques based on attainable historical and present information such that appropriate actions can be planned and carried out.
The aim is to quantitatively express the correlation between the factors. Incidence analysis is the basis for grey system analysis and forecast. To obtain quantitative grey information about the factors, the following grey transformation is first performed.

- It is assumed that m+1 behavioral sequences of a system are given by:

$$x_0 = (x_0(1), x_0(2), \dots, x_0(n));$$

$$x_1 = (x_1(1), x_1(2), \dots, x_1(n));$$

$$x_m = (x_m(1), x_m(2), \dots, x_m(n));$$

where x_0 is a sequence of data representing a system characteristic. These are called original behavioral sequences.

- Using the grey transformation, the following grey transformation sequences are obtained:

$$y_0 = (y_0(1), y_0(2), \dots, y_0(n));$$

$$y_1 = (y_1(1), y_1(2), \dots, y_1(n));$$

$$y_m = (y_m(1), y_m(2), \dots, y_m(n));$$

3. The differential information of grey incidence is defined as follows:
(Grey incidence coefficient). It is assume that $x_0 = (x_0(1), x_0(2), \dots, x_0(n))$; is a sequence of data representing a system characteristic, and for all i x_i is a sequence of relevant factors. For a given real number ξ∈ (0, 1), let:

$$\gamma(x_o(i), x_j(i)) = \frac{\min_{q=1}^{m} \min_{p=1}^{n} \left| x_0(p) - x_q(p) \right| + \xi \max_{q=1}^{m} \max_{p=1}^{n} \left| x_0(p) - x_q(p) \right|}{\left| x_0(i) - x_j(i) \right| + \xi \max_{q=1}^{m} \max_{p=1}^{n} \left| x_0(p) - x_q(p) \right|}. \tag{2}$$

The results show each factor makes a contribution to the evaluation. The value of the weight at a time point measures the influence of the coefficient on the system. A large value implies that the coefficient is more influential. The values of the weights are occasionally affected by the decision-makers subjectivity, which may result in certain faults. Determining the weights is a part of the decision-making process. In the paper, the maximum entropy method will be used for determining the weights of grey correlation coefficients and find the main influencing factors. The distribution of the weighted grey incidence coefficients is defined so that:

$$\gamma(x_0, x_j) = \frac{1}{n}\sum_{i=1}^{n}\gamma(x_0(i), x_j(i)). \tag{3}$$

Therefore, according to (2), the gray correlation value is calculated last, and the gray correlation coefficient is compared:

$$\Gamma_{0i} = \sum_{k=1}^{n}\left[w_k \times \gamma\big(x_0(k), x_i(k)\big)\right] \tag{4}$$

We give different definitions based on the results of the Weight value coefficient range, which is the difference between the maximum and minimum value in the given set in Table 1.

Table 1: Weight value coefficient range definition

Weight value	Definition
0.90-1	Very important
0.80-0.89	Important
0.70-0.79	Ordinary
Below 0.69	Not important

Source: This Study

4. Empirical Results and Analysis

The empirical analysis of this study mainly comprises two parts: First, this section adopts the DEA model to analyze the relative TE efficiencies of the schools by applying the DEA model. Then this study applies the GRA model to analyze the factors, including digital mobile e-learning factors, that affecting the relative efficiencies of schools (TE) in various counties and cities of Taiwan.

4.1 Results of Efficiency Analysis for DEA Mode

The efficiency analysis of this study primarily comprises three main sections. Section 1 describes the study objects and variables for inputs and outputs in this study. Section 2 presents the data description and correlation analysis between inputs and outputs. Finally, Section 3 analyzes the efficiency analysis of DEA model.

4.1.1 Study Objects and Variable for Inputs and Outputs in This Study

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

A. Study Objects

This study aimed to analyze whether the introduction of digital mobile e-learning increases schools' operational efficiency and whether 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 2:

Table 2: 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

Source: This Study

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 called into question. Hence, when applying DEA, the number of Decision-Making Units (DMUs) should be equal to or greater than the product of the number of inputs and the number of outputs. Otherwise, the efficiency estimated for each DMU through DEA would approximate 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 definitions of the input-output variables of public and private vocational schools in the four cities in Taiwan are listed in Table 3 and Table 4. There are five input variables: academic department, number of full-time teachers, number of part-time teachers, and staff; and three output variables: number of students, number of graduate’s students, and classes.

Table 3: 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 of full-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 of student	y_2	The number of graduates students.
7	classes	y_3	The number of school classes.

Source: This Study

Table 4: 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 of student	y_2	Output Indicator
7	classes	y_3	Output Indicator

Source: This Study

4.1.2 Correlation Analysis between Inputs and Outputs

This study employed Pearson correlation analysis to first analyze the degree of correlation between the input and output variables and remove 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

Source: This Study

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 of Technical (Total) Efficiency (TE)

As shown in Table 6 below, 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” 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 (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) failed to reach the efficiency rate of “1.” This result demonstrates that the introduction of digital mobile e-learning does not necessarily upgrade the 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.

Thus, we will apply the Grey Relational Analysis model to identify the factors, including digital mobile e-learning factors, that affect the relative efficiencies of schools (TE) in various counties and cities in Taiwan.

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

Source: This Study

4.2 Major Selected Factors Affecting School Efficiency through Innovative Teaching via Digital Mobile E-Learning

We take a different focus on the major factors of mobile digital e-learning that affect school efficiency. These factors concern the real situations/conditions and our recent research findings (Liu and Kuo, 2017), in which we applied the GRA model to investigate useful information on the factors promoting school efficiency. In this study, we focus on the major factors related to promoting promote the operational efficiency of school management through innovative teaching via digital mobile E-learning. The basic factors may be described as follows:

$\boldsymbol{TE_{it}}$: Technical efficiency for management of School $_i$during the period 2013 to 2015

$\boldsymbol{Z_1}_{it}$: School size (total numbers of school students) of School $_i$

$\boldsymbol{Z_2}_{it}$: Teacher-student ratio (average number of students per teacher) ofSchool $_i$

$\boldsymbol{Z_3}_{it}$: The total number of tablet PCs of School $_i$

$\boldsymbol{Z_4}_{it}$: Technical teacher ratio (measured by the ratio of the number of technicians as consultants teaching tablet PC knowledge to the total number of teachers in the school) of School $_i$

$\boldsymbol{Z_5}_{it}$: Total equipment expenses associated with tablet PCs of School $_i$

$\boldsymbol{Z_6}_{it}$: School $_i$ location dummy: in the northern area: 1, other areas: 0

$\boldsymbol{Z_7}_{it}$: School $_i$ attribute dummy: public high schools: 1, private high schools: 0

Finally, the basic model setups can be described as the following Equation (5) and eight representative indicators selected using GRA are subsequently and related to technical efficiency for management of school i, the functional relationship is as follows:

$$Y(TE_{it)} = f(\boldsymbol{Z_1}_{it}, \boldsymbol{Z_2}_{it}, \boldsymbol{Z_3}_{it}, \boldsymbol{Z_4}_{it}, \boldsymbol{Z_5}_{it}, \boldsymbol{Z_6}_{it}, \boldsymbol{Z_7}_{it}, \boldsymbol{Z_8}_{it}) \tag{5}$$

4.2.1 Research Analysis in GRA

The purpose of this part of the study is to facilitate comparative analysis by determining school efficiency and school characteristics. Thus, the examples of the application of this method in the works of Pei et al. (2009), Zhao et al. (1998 a, b), and Wang et al. (2010) were used to verify the validity of the proposed approach. Y ($\boldsymbol{TE_{it}}$) is the main behavioral sequence, and $\boldsymbol{Z_1}$, $\boldsymbol{Z_2}$, $\boldsymbol{Z_3}$, $\boldsymbol{Z_4}$, $\boldsymbol{Z_5}$, $\boldsymbol{Z_6}$, and $\boldsymbol{Z_7}$ are comparative sequences. Specific data are provided in Table 7:

Table 7: the grey incidence order is shown.

$\boldsymbol{Z_1}$	$\boldsymbol{Z_2}$	$\boldsymbol{Z_3}$	$\boldsymbol{Z_4}$	$\boldsymbol{Z_5}$	$\boldsymbol{Z_6}$	$\boldsymbol{Z_7}$
0.901	0.853	0.772	0.811	0.773	0.889	0.829

Source: This Study

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

(1) School size ($\boldsymbol{Z_1}$)

According to the empirical results shown in Table 7, the effects of school size on a school's operational efficiencies ($\boldsymbol{Z_1}$= 0.901 in GRA) is very important: School size has the greatest effect on TE. The results imply that the larger the school, the more economies of scale can be realized when outputs expand (such as teaching functions, research functions, and education or employment opportunities (enrollment rates)), thereby contributing to the school's operational efficiency.

(2) Teacher-student ratio ($\boldsymbol{Z_2}$)

Based on the empirical results shown in Table 7, the effect of the teacher-student ratio ($\boldsymbol{Z_2}$= 0.853 in GRA) on the school's operational efficiency (TE) is important, but not that important. One of the main reasons is that due to the problem of low fertility in Taiwan, the number of students (output variable) has been declining over the years, increasing the teacher-student ratio; reductions in the number of students lead to too many teachers as input in each school. Thus, it cannot raise the school's operational efficiency.

(3) Tablet PC numbers ($\boldsymbol{Z_3}$)

As can be seen from Table 7, the effect of tablet PC numbers ($\boldsymbol{Z_3}$ = 0.772 in GRA) on the school's operational efficiency (TE) is moderate. Clearly, innovative teaching affects school efficiency through the use of digital mobile e-learning with tablet PCs, which enable learners to be in the right place at the right time, that is, to be where they can experience the authentic joy of learning, which attracts students to learn. In fact, as the number of students declines, this leads to too many tablet PCs as input in each school. Thus, this variable cannot greatly raise the school's operational efficiency.

(4) Technical teacher ratio ($\boldsymbol{Z_4}$)

According to the results in Table 7, the effect of the technical teacher ratio of the efficiencies ($\boldsymbol{Z_4}$= 0.811 in GRA) on school's operational efficiency (TE) show is important, but not that important. In this role, teachers acting as technicians or consultants teaching tablet PC knowledge need to be able to identify the students' interests, relate these interests to the topic-related learning goals, and afford students opportunities to attain these goals based on the specific conditions a learner face. However, reductions in the number of students lead to too many teachers as input in each school. Thus, this variable cannot greatly raise the school's operational efficiency.

(5) Total equipment expenses associated with tablet PC ($\boldsymbol{Z_5}$)

According to the results in Table 7, the effects ($\boldsymbol{Z_5}$= 0.773 in GRA) associated with the total equipment expenses for tablet PCs on the school's operational efficiency are moderate. However, the costs are increasing of furnishing the related Internet and network equipment or devices to provide access to the internet, as well as the network equipment or devices to facilitate teaching and learning among teachers and students through digital mobile e-learning. Conversely, the number of students is reduced and leads to too many network equipment as input in each school. Thus, this variable appears not to raise the school's operational efficiency notably.

(6) School location: ($\boldsymbol{Z_6}$)

The effect of school location ($\boldsymbol{Z_6}$= 0.889 in GRA) on the school's operational efficiency (TE) is important, and can be seen in Table 7. In general, schools located in a metropolis (for example, Taipei City) can secure more resources. Clearly, the schools' accessory equipment comes from the budget of the first-tier city.

(7) School's status.: ($\boldsymbol{Z_7}$)

The effect of the school's public-private attribute ($\boldsymbol{Z_7}$= 0.829 in GRA) on its operational efficiency (TE) is important and shown in Table 7. In general, public schools' accessory equipment comes from the budget of the central government, but private schools must fund their accessory equipment from their own budgets; in other words, the more students, the greater the subsidy for a public school's accessory equipment. Clearly, the teaching quality in public high school, for example, makes it easier to apply mobile e-learning environments that use the latest technologies to introduce interactive learning environments into learning and teaching activities.

4.2.2 The Results for the Weights of the Grey Incidence Coefficients

Overall, first of all, the school size has been shown to be very important, followed by the teacher-student ratio, technical teacher ratio, school location, and school public-private attribute, all of which are classified as having important effects. Finally, the tablet PC numbers and total equipment expenses are shown to have moderate effects (Ordinary). Hence, the results are as follows:

$$\boldsymbol{Z_1} > \boldsymbol{Z_6} > \boldsymbol{Z_2} > \boldsymbol{Z_7} > \boldsymbol{Z_4} > \boldsymbol{Z_5} > \boldsymbol{Z}_3$$

5. Concluding Remarks

In this study, we first applied data envelopment analysis (DEA) to analyze the operational efficiency of high schools in Taiwan, then used the GRA model to find the main influencing factors.

Based on our empirical results from the 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. All these schools are located in Taipei City or New Taipei City. However, we did not know which factors affect digital mobile e-learning.

Thus, we also applied the GRA model to find the factors affecting the school's operational efficiency. These results show a clear and important relationship between the school size, teacher-student ratio, technical teacher ratio, school location, and school high-vocational attribute as important determinants affecting the efficiency of school management. Among these, the school size seems to be most closely connected to digital mobile e-learning.

In order to increase students' learning effectiveness and enhance the school's operational efficiency based on the results of this study, it is necessary to first note that school size is important. Second, other factors to change are the teacher-student ratio, technical teacher ratio, school location, and school high-vocational attribute. The results of this research can also serve as a reference for educational authorities when formulating policies and regulations to promote digital mobile e-learning.

Lastly, the conclusions and recommendations presented here are based on the models constructed, sample data collected, and research methodologies employed in 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 a particular district of Taiwan, to further tailor any application of our findings so as to yield more accurate conclusions.

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