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Evaluating the Digital Transformation Performance of Retail by the DEA Approach

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Abstract: In recent years, under the impact of digitization, all industries around the world have undergone unprecedented changes. Such changes have not only altered people's consumption behavior but have also forced enterprises to accelerate the pace of digitization and actively start digital transformation. In this study, a literature review and focus group interview (FGI) were used to develop the dimensions and criteria to assess enterprise digital transformation status. To illustrate the digital transformation criteria proposed in this research, the retail industry was used as an example to measure the overall digital transformation performance by data envelopment analysis (DEA). The results show that the poor technical efficiency demonstrated by a vendor was not only due to the gradually decreasing returns to scale of the market; a decline in pure technical efficiency was also a contributor. In addition to adjusting their production on the basis of market conditions, vendors should properly manage their internal operations and pay attention to their resource and scale allocations to prevent reductions in their pure technical efficiency.

Keywords: digital transformation; assessment indicator; focus group interview; data envelopment analysis; e-survey

MSC: 90-XX; 90Bxx; 90Cxx

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1. Introduction

Given the trend of digital transformation sweeping the world, many digitally native enterprises continue to grow rapidly, earn higher profits than before and trigger paradigm shifts in their industries. The risks of investing in digital transformation have remained one of the biggest concerns for senior executives when planning company growth strategies. As reported by Forbes, in as many as 70% of digital transformations, the targets of the transformation are not reached. Furthermore, in digital transformation projects worth as much as 1.3 trillion USD, as much as 900 billion USD is wasted [1]. An examination of the cause of this waste reveals that digital transformations must be promoted on a range of levels and that, despite many enterprises being interested in digital transformation, they have no idea where to begin. Furthermore, enterprises that have already begun their digital transformation need to be able to measure their transformation progress and understand in what ways they are different from their peers in the industry [2,3].

Industrial, government and academic papers and reports [3–5] have proposed many benchmarks for measuring digital transformation performance and have applied these benchmarks in the evaluation of enterprises' digital transformation maturity. However, existing evaluation approaches fail to help enterprises determine their performance relative to their peers or how they can adjust their investment in specific digital transformation projects. To provide a solution to such problems, this study proposes a method for calculating the production or implementation efficiency of an enterprise in its promotion of digital transformation operations by considering relevant metrics. The adjustment value that an enterprise should then make in specific digital transformation projects was then estimated. Several quantitative analysis tools are employed in the literature on production or implementation efficiency. These quantitative analyses can generally be divided into parametric and nonparametric approaches. The most representative parametric approach is the stochastic frontier approach, in which the function type and the random interference items of the production function must be assumed in advance. The most well-known nonparametric approach is data envelopment analysis (DEA), which does not require prior assumptions about the production function type and can handle multiple inputs and outputs. Consequently, scholars have already applied DEA to analyze the efficiency of digital transformations. However, the related studies mostly assessed efficiency on the national decision-making level. For example, the authors of [6] used a DEA-based model to analyze the dynamics and the level of digital information in Western Balkan Countries. The authors of [7] used DEA to measure the efficiency of technological catch-up in 57 countries. The authors of [8] measured digital literacy to create a useful index. The DEA method was also used for ranking in the literature [9]. The authors of [10] measured the efficiency and rank the high-tech economies of 50 US states through DEA. The authors of [11] applied DEA to measure the impact of ICT on labor productivity growth in the period from 1995 to 2005 in 14 OECD member countries. The author of [12] applies the DEA method in combination with the Malmquist Productivity Index to measure the effectiveness of digital economy development in the EU, Central and Eastern Europe and the Western Balkans through the analysis of the dynamics and level of digital information. To the best of authors' knowledge, no literature has been found to provide the study of the performance of retail units in digital transformation.

In this study, we performed a literature analysis and held focus group interviews (FGI) to identify the inputs and outputs used by enterprises to promote digital transformation performance. Subsequently, we used DEA to measure the overall digital transformation performance of several Taiwanese retailers. FGIs have often been used to identify major factors [13–15], and they enable researchers to interact with interviewees and cross-compare their responses through triangulation. Additionally, DEA enables the simultaneous processing of multiple inputs and outputs and has been widely applied in various topics related to decision making. Basically, there are two types of models in DEA: radial and non-radial. Radial models are represented by the CCR model developed by Charnes, Cooper and Rhodes, and they are based on proportional changes in the levels of inputs or outputs [16]. In contrast, non-radial models such as the slacks-based measure of efficiency (SBM) model do not handle proportional changes in inputs or outputs but do handle specific slacks for each input or output [17]. In other words, if the loss of the original proportionality is inappropriate for the analysis, it becomes a shortcoming for non-radial models [18]. In our study, we considered that retailers may not simply concentrate their efforts on improving the results in one dimension of the digital transformation output to a greater extent than in the other. Therefore, we selected a radial measurement of efficiency rather than an SBM model.

The implementation procedures used in this study are illustrated using the example of the retail industry, and the process and results of assessing the enterprises' digital transformation performance are discussed in detail in this paper. The main contributions of this study are as follows. First, on the basis of the literature and interviews with digital transformation experts and managers in Taiwan's retail businesses, this study defines the inputs and outputs for assessing an enterprise's digital transformation performance. Second, a performance evaluation approach applicable for any enterprise's digital transformation and for helping enterprises minimize the risks associated with digital transformation is proposed. This paper has five sections: the introduction, which presents the research motivation and purpose; an explanation of DEA; details on the research design and analytical procedures; a presentation of the empirical results; and the study's conclusions.

2. Research Methodology

Data Envelopment Analysis

DEA was proposed by [19] as a nonparametric method for calculating efficiency frontiers without the use of preset function types. DEA is mainly used to evaluate the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. Within DEA, productive efficiency is defined as the product of technical efficiency and price efficiency. Technical efficiency refers to the effective use of production factors, given existing techniques, to maximize the outputs, whereas price efficiency is the appropriate allocation of production factors to minimize costs, given existing techniques and prices. Building on Farrell's concepts and on the basis of the concept of one output with multiple inputs, ref. [16] proposed the use of linear programming techniques to estimate the relative efficiency of multiple inputs and outputs; this became what is currently known as the CCR model. The authors of [20] developed the BCC model by removing the fixed-returns restriction in the CCR model and by decomposing technical efficiency into pure technical efficiency and scale efficiency. The CCR model in DEA can be summarized as follows:

Assuming that the ith input (I = 1, ... , m) in DMU$_j$ (j = 1, ... , n) is X_{ij} and the rth output (r = 1, ... , s) is Y_{rj}, the efficiency of DMU$_\mathrm{k}$ can be obtained from Equation (1).

$$\begin{aligned} & E_k = Max\ \frac{\sum\limits_{r=1}^{s} u_r Y_{rk}}{\sum\limits_{i=1}^{m} v_i X_{ik}} \\ & s.t.\ \ \frac{\sum\limits_{r=1}^{s} u_r Y_{rj}}{\sum\limits_{i=1}^{m} v_i X_{ij}} \le 1,\ \ u_r, v_i \ge \varepsilon > 0,\ j = 1, \ldots, \mathrm{n} \end{aligned} \tag{1}$$

where u_r and v_i represent the weights of the r-th output item and the i-th input item, respectively, n is the number of DMUs, m is the number of inputs, s is the number of outputs and ε is a minimal positive value, which is called the non-Archimedean small number by [16]. The efficiency value of Equation (1) is used to compare the efficiency of input resources under the same output level, so it is called input-based efficiency. This model limits the ratio of output to input to be within one, and its feature is used to treat the weights u_r and v_i as unknown. When calculating the target decision-making unit $_k$, the weight is selected as a specific value to maximize the efficiency value E_k. Since the decision-making units choose the most favorable weights u_r and v_i, the analysis results are also relatively objective.

$$\begin{aligned} & E_k = Max \sum_{r=1}^{s} u_r Y_{rk} \\ & s.t.\ \ \sum_{i=1}^{m} v_i X_{ij} = 1 \\ & \qquad \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0,\ \ u_r, v_i \ge \varepsilon > 0,\ j = 1, \ldots, \mathrm{n} \end{aligned} \tag{2}$$

Since the objective function of Equation (1) is fractional linear programming, which is not only difficult to operate but also has the risk of an infinite solution, we can convert the equation into the form of linear programming (Equation (2)), i.e., set the denominator to one to form an input-based primitive problem. The main purpose of such a linear transformation is to avoid the occurrence of multiple solutions. In order to obtain more information, we can transform the linear problem of Equation (2) into a dual problem (Equation (3)), where s_i^-, s_r^+ represent the slack variable of the ith input variable and the surplus variable of the r output variable, respectively, which are the variables commonly used to transform inequalities into equations in linear programming. The variable θ_k represents the radial efficiency value of the $\mathrm{DMU_k}$, and for the $\mathrm{DMU_k}$, the θ_k value is between zero and one. h_k represents the relative efficiency of the $\mathrm{DMU_k}$.

$$\begin{aligned} & Min\ h_k = \theta_k - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\ & s.t.\ \ \sum_{j=1}^{n} \lambda_j X_{ij} - \theta_k X_{ik} + s_i^- = 0 \\ & \qquad \sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = Y_{rk},\ \lambda_j, s_i^-, s_r^+ \geq 0 \end{aligned} \tag{3}$$

3. Research Scheme and Metrics Confirmation

3.1. Research Scheme

Figure 1 shows the research framework of this study. After reviewing the literature and obtaining the preliminary measurement indicators of enterprises' performance in promoting digital transformation, FGI is first used to confirm the input and output items to evaluate the performance of enterprises' digital transformation. After that, relevant data are collected and integrated into the DEA model of the second stage to truly understand the relative efficiency value of each enterprise in promoting digital transformation.

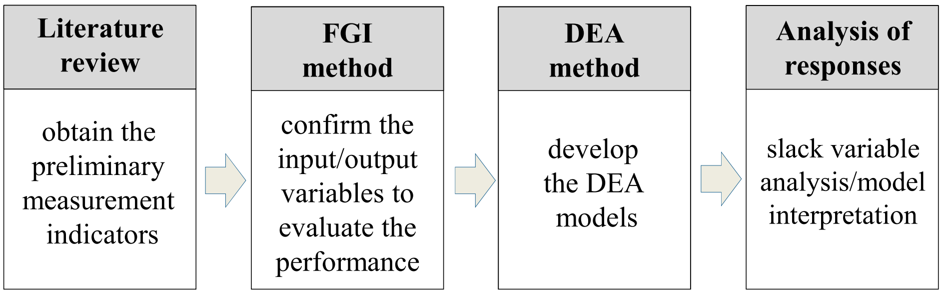

Figure 1. Research scheme.

3.2. Developing Digital Transformation Dimensions and Metrics

Digital transformations affect industry competition and national economic development. These transformations are a major force behind the global economic revolution. Consequently, digital transformations have been a popular topic in Taiwanese, industrial and academic research. However, inconsistencies in the literature exist in the definition and interpretations of digital transformation, and none of the proposed sets of digital transformation metrics for enterprises have been widely accepted. Nevertheless, scholars appear to agree on the dimensions of the measurement of digital transformations. For instance, ref. [21] asserts that digital maturity is the joint product of strategy, culture and leadership and that an organization's culture must embrace the importance of applying data and analytics to decision making and business processes. Reference [4] proposes that a digital transformation has four major dimensions: the use of technologies, changes in value creation, structural changes and financial support. From their digital transformation case studies, ref. [22] discovered that the push toward digital transformation is significantly influenced by management's perception of the digital transformation. The consultancy firm Deloitte [3] measured the extent of an enterprise's digital transformation by considering five major dimensions: the customer, strategies, technologies, operations and the corporate culture. Reference [23] states that, in the push toward a digital transformation, business leaders should focus on the following concrete tasks or projects: recruiting and fostering talents with digital and analytical capabilities, investing time and money, rapidly adjusting digital strategies in response to market changes, clearly defining employee roles and empowering employees. The consultancy firm McKinsey conducted a survey in 2018 and summarized five key factors in a successful digital transformation: leaders who understand technology, the training of employees in relevant capabilities, the empowerment of employees to try new methods, the normalization of the use of digital tools within the organization and the use of digital methods for regular communication. The digital transformation consultancy OOSGA [24] further states that the implementation of a digital transformation should emphasize the digital strategy and its implementation, the organization and culture, talents and capabilities, data management and analytics, and technology and tooling. The government of South Australia further proposed a Digital Transformation Toolkit [25] that can be employed to measure the progress of an enterprise's digital transformation in five dimensions: governance and leadership, organizational culture, resources and capabilities, innovation and the use of technologies.

To develop a set of dimensions and indicators for measuring an enterprise's digital transformation, we compiled a preliminary topology (digital transformation technologies, organizational operations, process optimization, customer experience and business models) based on a digital transformation scoreboard [26] and the literature's definition of digital transformation and compiled the possible metrics that can be employed within each dimension. For example, because digital transformation is a strategy implemented in response to industrial competition and in pursuit of sustainable growth, this strategy must be both agreed upon by management and accepted and used by employees if it is to be coordinated and executed across the organization. Consequently, the organizational operations dimension should include measurements of managerial agreement and cross-organizational operations. Furthermore, for business executives to create strategies based on analytical data, they must recognize the value of data utilization and construct digital infrastructure to collect data in real time; as such, the dimension of digital transformation technologies should include metrics regarding the value of data.

Regarding the application of digital technologies, some researchers and industries consider that digital transformation is the ongoing process of using digital technologies to collect and analyze data to improve an enterprise's internal and external operations and decision making [27–31]. Consequently, whether an enterprise possesses the infrastructure to support a digital transformation (such as an information system and the supporting software and hardware); whether the enterprise has data gathering, analytical and utilization capabilities; and whether the enterprise understands how digital technologies can be used to improve its internal processes (such as purchase orders, procurement, logistics and warehousing) and external processes (such as supply chains, sales channels and customer service), digital technologies may be employed for measuring the enterprise's digital transformation. Furthermore, many multinational enterprises during a digital transformation agree that such a transformation is an ongoing reformation across the organization that builds ecosystems and innovates business models while triggering changes in organizational culture, value chains, value propositions and customer experiences [32]. Therefore, this study concludes that digital transformation metrics should include items, such as whether the organization has a digital culture, the extent to which ecosystems are constructed through data exchange, commitment to improving the customer experience and the extent of the reformation and innovation of business models. Furthermore, given that the amount of resources an enterprise invests in its digital transformation affects the transformation's progress, this study concludes that invested resources (such as personnel, funds and training) should be listed as input items in the evaluation of an enterprise's digital transformation performance.

3.3. FGI and Confirming the Digital Transformation Metrics

First, we compiled industrial reports and the academic literature and extracted dimensions and indicators that enterprises should consider when measuring their digital transformation performance. FGI questions were then developed based on these dimensions and indicators. An FGI was conducted to verify the suitability of the dimensions and indicators and to select the final inputs and outputs. Following the suggestions in the literature, this study used purposive sampling to select focus group members with relevance to the research topic. Our focus group members were six managers of a digital transformation department in a major retail vendor and eight scholars studying digital transformation. The focus group members had to have at least 15 years of work experience and a recognized career in the field of data analytics or business management.

The FGI was held in the conference room of a national university in Taiwan and lasted approximately 3 to 3.5 h. Prior to the FGI, we informed a professional moderator with knowledge of digital transformations about the purpose of this study, the results of the literature review and that the semi-structured FGI script had been drafted on the basis of the preliminary digital transformation typology we had developed from the literature review. Under the guidance of the principal investigator and supervision of the professional moderators, the focus group discussed a theme—"developing enterprise digital transformation metrics in accordance with five main dimensions (digital transformation technologies, organizational operations, optimizing processes, customer experiences and business models)"—and identified the strategies and approaches that were used by enterprises that had successfully undergone a digital transformation. For each dimension, the main question discussed by the focus group participants was "What is the most critical indicator for measuring an enterprise's digital transformation?" Other questions included "What are the impacts of investments, full-time staff and training on an enterprise's progress in a digital transformation?"; "In your opinion, what changes in organizational operations are beneficial to an enterprise's digital transformation?"; and "What are the differences between focusing on customer experiences and simply emphasizing business goals?".

With the consent of the participants, the entire duration of the FGI was recorded. The audio and video recordings were stored anonymously and were only permitted to be used in this study. All recordings were transcribed into text files. Observers of the FGI also made notes in real time. To ensure the accuracy of the transcription, after the FGI, the transcripts were compared with the audio recordings. The unedited transcripts were 57 A4 pages long. Following the approaches described by [33,34], we performed a qualitative content analysis of the transcripts. First, we identified meaningful metrics of digital transformation on the basis of the contents, definitions and general driving processes of digital transformations [35]. Second, we condensed these meaningful metrics and tagged the metrics with codes; metrics tagged with the same code were then grouped together to form dimensions. In the last step, after repeatedly reading the transcripts, we summarized the input and output measures in this study in Appendix A.

As shown in Appendix A, all variables are consistent with the measurement in the digital transformation scoreboard data [26] published annually by the European Commission, where the ratio of existing digital transformation talents (RDTT) and the ratio of invested funds in digital transformation (RIFDT) were selected as input variables, mainly because most focus group members believed that sufficient investment can offer an exploratory overview of the successful implementation of digital technologies in the retail industry [22]. Regarding the ratio of the training hours of digital transformation (RTHDT), most focus group members placed it at the forefront of the digital transformation process because of the learning needs to develop the required competencies for enabling a successful transformation [36]. With respect to the five output variables from the digital transformation scoreboard [26], digital transformation technologies (DTT), organizational operations (OO), process optimization (PO), customer experiences (CE) and business models (BM), they were determined mainly because most focus group members believed that they could effectively show the effects and levels of digital transformation in enterprises [26].

4. Empirical Study

4.1. Data Collection

Once the variables and indicators were selected, this study conducted an e-survey for data collection, thereby providing the respondents with sufficient time to respond and thus minimizing the disruptions to respondents from the researchers [37,38]. We used Likert scales to assess participants' responses to the output indicators in each dimension, i.e., respondents' impressions of digital transformation results. The typical Likert scale is a 5- or 7-point ordinal scale used by respondents to rate the degree to which they agree or disagree with a statement [39]. In this study, the Likert scales had ranges from 1 (strongly disagree) to 5 (strongly agree). The participants chose the number which suited them the best to define their perceived digital transformation results. Additionally, 120 managers in a medium or large retail enterprise that had implemented a digital transformation were invited over the phone to participate in the study to ensure the representativeness of the gathered data. We chose not to contact and consult individuals about their willingness to participate in advance; rather, access to the questionnaire was provided after the prospective respondent had accepted our invitation to participate. The survey period was from middle to late January of 2022. Given the questionnaire content and that some questions pertained to the resource inputs and outputs of enterprises during their digital transformation, only 92 survey responses were completed. On the basis of data integrity and the DEA condition that DMU data must demonstrate homogeneous relationships, we selected 62 enterprises with mean capital between 8.52 million USD and 12.65 million USD as the study sample.

Table 1 provides the summary statistics of the input and output variables. Table 1 also shows that the variance of some input or output variables are large. The variables having the largest standard deviation of input and output variables are the ratio of the training hours of digital transformation (RTHDT) and the digital transformation techniques (DTT), respectively. Figure 2 illustrates the boxplots for all five output variables. The line across the box represents the median, whereas the bottom and top of the box show locations of the first and third quartiles (Q1 and Q3). The whiskers are the lines that extend from the bottom and top of the box to the lowest and highest observations inside the region defined by Q1 - 1.5(Q3-Q1) and Q3 + 1.5(Q3-Q1), and individual points with values outside these limits (outliers) are plotted with asterisks [40]. Boxplots provide a visual impression and the shape of the underlying distributions. For example, boxplots (such as that for BM) indicate that the underlying distribution is skewed towards higher levels. By inspecting these plots, it was possible to perceive differences among the five DT results. For example, retailers have a high degree of digital transformation success on PO metrics and have a low degree of digital transformation success on CE and BM metrics. The high degree of digital transformation success on PO metrics is most likely because the company's workflows could be digitized or optimized without too much technical knowledge.

We aggregated each vendor's indicator scores separately and then calculated the mean scores. Then, we calculated the Pearson coefficients of correlation between the input and output data to determine whether there were correlations between the inputs and outputs.

Items conformed to the assumption of isotonicity (Table 2). The results revealed moderate to strong correlations among the input and output variables and that these correlations were isotonic. This indicated that, when the value of an input variable increased, the value of the output variable also increased. The requirement was that the relationship between inputs and outputs must not be erratic. Increasing the value of any input while keeping other factors constant should not decrease any output but should instead lead to an increase in the value of at least one output.

Table 1. Summary statistics of variables (N = 62).

Variables	Mean	Std. Dev.	Min.	Max.
RDTT (x_1)	0.157	0.055	0.000	0.200
RIFDT (x_2)	0.089	0.004	0.068	0.090
RTHDT (x_3)	0.254	0.385	0.000	1.000
DTT (y_1)	1.820	0.816	1.000	4.667
OO (y_2)	1.583	0.698	1.000	4.000
PO (y_3)	1.711	0.554	1.000	3.222
CE (y_4)	1.204	0.437	1.000	3.000
BM (y_5)	1.327	0.711	1.000	5.000

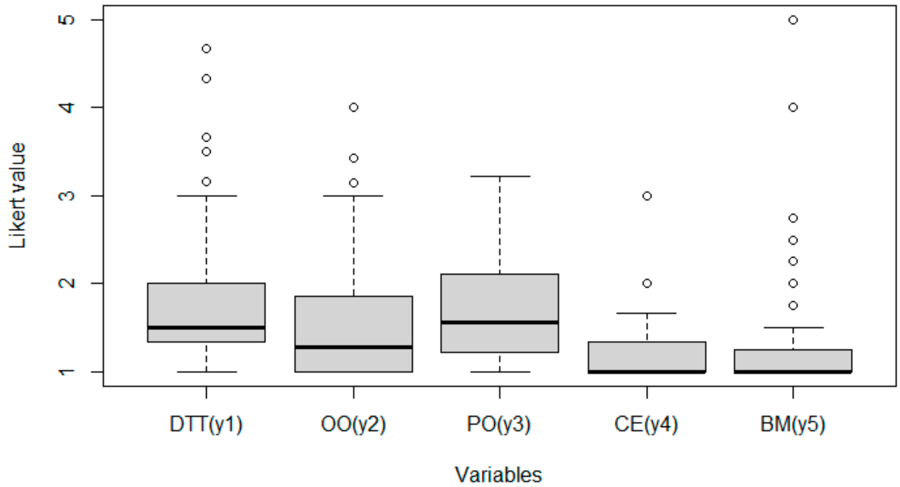

Figure 2. Boxplot of the output variables.

Table 2. Correlation of input and output variables.

	RDTT (x_1)	RIFDT (x_2)	RTHDT (x_3)	DTT (y_1)	OO (y_2)	PO (y_3)	CE (y_4)	BM (y_5)
RDTT (x_1)	1.000	—	—	—	—	—	—	—
RIFDT (x_2)	0.371	1.000	—	—	—	—	—	—
RTHDT (x_3)	0.190	0.329	1.000	—	—	—	—	—
DTT (y_1)	0.195	0.026	0.231	1.000	—	—	—	—
OO (y_2)	0.003	0.004	0.251	0.735	1.000	—	—	—
PO (y_3)	0.139	0.072	0.340	0.731	0.765	1.000	—	—
CE (y_4)	0.137	0.010	0.272	0.450	0.632	0.634	1.000	—
BM (y_5)	0.054	0.017	0.195	0.647	0.625	0.481	0.248	1.000

4.2. Analyzing the Efficiency of Digital Transformations by Retail Vendors

This study used DEA to estimate the efficiency of 62 retail vendors' efforts in digital transformation. When selecting a DEA model, there are typically two considerations: the purpose of the analysis and the properties of the inputs and outputs. In this study, our goal was to compare the total efficiency values of 62 Taiwanese retail vendors and to understand the causes of any inefficiencies. We therefore decided to use the CCR model, which calculates the constant returns to scale (CRS), to determine the total efficiency values (as the value increases, the vendor becomes more efficient) and the BCC model, which calculates the variable returns to scale (VRS), to determine the technical efficiency values (whether the resources invested by the analyzed vendor were used optimally to minimize costs and maximize efficiency at their actual production scale). The DEA results are presented in Table 3. We found that the mean efficiency value among the 62 retail vendors was approximately 0.175, and the standard deviation was 0.307. The highest efficiency value was 1, and the lowest was 0.002. Only six DMUs (DMU_2, DMU_{37}, DMU_{39}, DMU_{41}, DMU_{47} and DMU_{59}) were revealed to be efficient, accounting for only 9.7% of all DMUs. It is noted that, although these retailers' outputs are almost the same as the mean outputs of the group, these retailers consume relatively lower levels of inputs and hence turn out to technically be very efficient. The analysis results for the vendors' overall technical efficiencies, technical efficiencies and scale efficiencies are also presented in Table 3. Among the 56 vendors with overall technical efficiency that did not reach 1, more than half (such as DMU_5, DMU_{12} and DMU_3) had poor technical efficiency due to suboptimal scale efficiency. Businesses should thus invest in their digital transformation on the basis of actual market conditions and not blindly expand their investment, which may result in a decline in efficiency. Poor technical efficiency was the reason the other half of vendors had an overall technical efficiency lower than 1 (such as DMU_{43}, DMU_{35} and DMU_9). These vendors should strengthen their internal audits of digital transformation budgets and the delegation of digital transformation staff to determine any decision errors that were made and why they were made.

Table 3. Efficiency value of each retail vendor.

DMUs	OTE	TE	SE	RTS	DMUs	OTE	TE	SE	RTS
1	0.109	1.000	0.109	drs	32	0.030	0.622	0.048	drs
2	1.000	1.000	1.000	-	33	0.017	0.651	0.026	drs
3	0.445	1.000	0.445	irs	34	0.018	0.622	0.029	irs
4	0.314	0.973	0.322	drs	35	0.028	0.563	0.050	drs
5	0.864	1.000	0.864	drs	36	0.017	0.700	0.024	drs
6	0.178	1.000	0.178	irs	37	1.000	1.000	1.000	-
7	0.005	0.725	0.007	irs	38	0.015	0.571	0.026	drs
8	0.091	1.000	0.091	drs	39	1.000	1.000	1.000	-
9	0.044	0.549	0.080	drs	40	0.022	1.000	0.022	irs
10	0.084	0.706	0.118	drs	41	1.000	1.000	1.000	-
11	0.173	0.818	0.212	irs	42	0.033	0.771	0.043	drs
12	0.528	1.000	0.528	drs	43	0.011	0.569	0.020	drs
13	0.002	0.498	0.004	drs	44	0.018	0.767	0.023	drs
14	0.255	1.000	0.255	drs	45	0.012	0.846	0.014	drs
15	0.131	0.576	0.228	drs	46	0.064	1.000	0.064	drs
16	0.196	1.000	0.196	drs	47	1.000	1.000	1.000	-
17	0.011	0.538	0.020	drs	48	0.160	1.000	0.160	drs
18	0.026	0.541	0.048	drs	49	0.181	1.000	0.181	drs
19	0.020	0.572	0.035	drs	50	0.051	0.705	0.072	drs
20	0.027	0.569	0.047	irs	51	0.080	1.000	0.080	drs
21	0.030	0.672	0.045	drs	52	0.014	0.616	0.023	irs
22	0.067	1.000	0.067	drs	53	0.017	0.477	0.035	drs
23	0.029	0.745	0.038	drs	54	0.013	0.543	0.024	drs
24	0.008	0.689	0.012	drs	55	0.021	0.512	0.040	drs
25	0.023	1.000	0.023	drs	56	0.031	0.726	0.043	drs
26	0.012	1.000	0.012	irs	57	0.072	0.890	0.081	drs
27	0.005	0.682	0.008	drs	58	0.016	0.569	0.029	drs
28	0.008	0.478	0.016	drs	59	1.000	1.000	1.000	-
29	0.024	0.642	0.037	drs	60	0.059	0.730	0.081	drs
30	0.028	0.570	0.049	drs	61	0.058	0.571	0.101	drs
31	0.021	0.977	0.022	drs	62	0.026	0.634	0.041	drs

OTE: overall technical efficiency; TE: Technical efficiency; SE: Scale efficiency; RTS: Returns to scale. -: optimal scale; drs: decreasing returns to scale; irs: increasing returns to scale.

In Table 3, the calculations of returns to scale (RTS) in the 5th column have a direct interpretation with respect to sound investment in a productive workforce and in training hours dedicated to the digital transformation. It is also clear that a retailer with decreasing returns to scale (DRS) is not using its investment optimally, whereas a retailer with IRS can be expected to be engaged in rapid digital transformation growth and higher digital transformation outputs. This DRS inefficiency for other retailers means that it is possible for these retailers to reduce the use of their inputs while still obtaining the same amounts or more of the outputs in digital transformation technologies (DTT), organizational operations (OO), process optimization (PO), customer experiences (CE) and business models (BM) dimensions. In additions, as shown in Table 3, DMU_3, DMU_6, DMU_7, DMU_{11}, DMU_{34} and DMU_{40} show increasing returns to scale (IRS). The presence of IRS implies that these DMUs enjoy higher outputs with respect to using their investment in recruiting digital transformation staff and in education and training due to their highly productive factors of production. This situation may spur retailers to invest more in digital transformation, which is seen as a sound investment in a productive workforce and in education and training. However, both DRS and IRS are considered inefficient scale sizes. The most optimal use of resources is operating at CRS or scale size 1.

4.3. Slack Variable Analysis

Projection analysis involving the slack variables and total efficiency values determined using the CCR models was performed to identify where Taiwanese retail vendors can make improvements to the efficiency of their digital transformation tasks and to the resources invested in those tasks. Using the equation $X^{*}_{ik} = \theta^{*} X_{ik} - s_i^{-*}$, we calculated the management and control targets of each vendor, i.e., the suggested input amount (X^{*}_{ik}). Here, θ^{*} is the total efficiency of the DMU, X_{ik} is the original input variable and s_i^{-*} is the slack variable. We then analyzed the slack variables of individual retail vendors on the basis of these analysis results and the vendors' original input data.

The slack variable represents the amount by which a relatively inefficient vendor should decrease its inputs to increase its relative efficiency. The suggested input improvement was ΔX_{ik} and is calculated using the equation $\Delta X_{ik} = X_{ik} - X^{*}_{ik}$. The analysis results are presented in Table 4. For DMU_3, we determined that the ratios of digital transformation personnel and digital transformation training should be reduced by 0.075 and 0.076, respectively. Next, the efficiency of each retail vendor's input variables was recalculated using the recommended values to confirm that these analysis results were the optimal adjusted values. According to the findings, the total efficiency values were all the optimal efficiency value, which was 1, whereas the slack variables had the value of 0. The technical efficiencies and scale efficiencies in the BCC model were also 1, the optimal efficiency value. Due to the hypotheses and application limitations in this study, the methods employed in this paper are only applicable to samples with high levels of homogeneity. The present method only enabled the analysis of "relative" efficiency rather than "absolute" efficiency. Consequently, a DMU that was assigned an efficiency value of 1 (indicating optimal efficiency) was not necessarily a truly efficient unit. A DMU that is identified as being inefficient must analyze its slack variables to adjust its input variables before it can increase its efficiency to a relatively high level.

Table 4. Analysis results of inefficient DMUs.

DMU	RDTT	RIFDT	PDTT	DMU	RDTT	RIFDT	PDTT
1	0.000	0.001	0.000	30	0.084	0.000	0.000
3	0.075	0.000	0.076	31	0.204	0.000	0.000
4	0.094	0.087	0.000	32	0.063	0.085	0.000
5	0.077	0.086	0.000	33	0.303	0.000	0.000
6	0.052	0.080	0.277	34	0.130	0.000	0.000
7	0.064	0.150	0.056	35	0.190	0.000	0.000
8	0.000	0.090	0.000	36	0.314	0.000	0.000
9	0.054	0.000	0.000	38	0.298	0.000	0.000
10	0.040	0.000	0.000	40	0.053	0.087	0.000
11	0.000	0.000	0.623	42	0.157	0.000	0.000
12	0.082	0.059	0.000	43	0.223	0.014	0.000
13	0.501	0.250	0.116	44	0.062	0.000	0.000
14	0.076	0.076	0.000	45	0.030	0.016	0.000
15	0.003	0.000	0.000	46	0.000	0.003	0.000
16	0.058	0.081	0.732	48	0.000	0.095	0.000
17	0.275	0.004	0.000	49	0.064	0.073	0.000
18	0.068	0.000	0.000	50	0.000	0.000	0.266
19	0.228	0.000	0.000	51	0.000	0.064	0.000
20	0.015	0.004	0.000	52	0.412	0.001	0.055
21	0.000	0.010	0.107	53	0.022	0.016	0.070
22	0.076	0.093	0.000	54	0.378	0.005	0.000
23	0.003	0.000	0.000	55	0.185	0.010	0.000

Table 4. *Cont.*

DMU	RDTT	RIFDT	PDTT	DMU	RDTT	RIFDT	PDTT
24	0.487	0.037	0.000	56	0.146	0.000	0.000
25	0.098	0.000	0.000	57	0.047	0.000	0.000
26	0.000	0.045	0.000	58	0.310	0.005	0.000
27	0.254	0.133	0.000	60	0.095	0.057	0.000
28	0.396	0.050	0.039	61	0.052	0.000	0.000
29	0.080	0.015	0.000	62	0.011	0.012	0.025

5. Conclusions

The urgency of digital transformation varies from industry to industry, and enterprises set different standards of progress in response to the different competitive situations they face. Consequently, determining how appropriate ratios and priorities can be set for digital transformation investment while digital transformation tasks are promoted can help enterprises improve the effectiveness of their digital transformation [41]. This study employed the retail industry as an example to illustrate the definitions of digital transformation metrics and methods for evaluating digital transformation performance. The retail industry was selected because it is one of the oldest industries, as well as an essential one. Due to its broad inclusion of basic-level workers, the retail industry has constantly served as a major indicator of socioeconomic development. Furthermore, lockdown measures during the COVID-19 pandemic have accelerated the shift toward online consumption, resulting in retailers being unable to keep up with trends and implement the necessary digital upgrades to face bankruptcy or restructuring. For these retailers, digital transformation is mandatory to ensure survival.

In a sample of medium-sized retail vendors, this study used DEA to investigate enterprises' efficiency in implementing a digital transformation. To demonstrate the effectiveness of our proposed method, we conducted an empirical study using data from 62 Taiwanese retail vendors. Some of the vendors (DMU_5, DMU_{12}, DMU_3, DMU_{14}, DMU_{16}, DMU_{49} and DMU_6) were discovered to be inefficient because of poor scale efficiency, whereas others (DMU_{43}, DMU_{35}, DMU_9, DMU_{54}, DMU_{18}, DMU_{17} and DMU_{55}) performed poorly because of their technical inefficiency. Overall, the poor technical efficiency demonstrated by a vendor was not only due to the gradually decreasing returns to scale of the market; a decline in pure technical efficiency was also a contributor. In addition to adjusting their production on the basis of market conditions, vendors should properly manage their internal operations and pay attention to their resource and scale allocations to prevent reductions in their pure technical efficiency.

Although this study mainly employed radial measures in its evaluation of retail vendors' implementation of a digital transformation, non-radial approaches such as the Russell measure and non-oriented slack-based measures are also applicable. Therefore, subsequent scholars can consider applying non-radial measures to evaluate the performance of retail vendors implementing a digital transformation under the condition that the most appropriate proportion adjustments can be made for each input and output. Given that DMU data must demonstrate homogeneous relationships, not all retail vendors in Taiwan were included in this study's data sample and evaluation. To prevent problems caused by an insufficiently large data sample, scholars can consider the use of meta frontier approaches for analyzing the operational performance of DMUs of different scales.

Moreover, it must be noted that DEA is not completely flawless. The first limitation of this study is that the DEA method is based on extreme points and compares each unit to the best performers. This particular feature makes DEA more sensitive to data noise and measurement errors. The second limitation of DEA is that, when using the CCR model, there are more DEA efficient DMUs if the number of DMUs is not relative enough to the number of indicators. This situation leads to a low capability of discernment. To solve this problem, the DEA super-efficiency model can possibly be considered.

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Appendix A

Table A1. Dimensions of the retail vendor digital transformation progress framework and their corresponding indicators.

	Variables/Dimensions	Indicators	Calculation/Question Statement
Inputs	Ratio of existing digital transformation talents (RDTT)	-	RDTS = existing digital transformation talents/the total number of employees
	Ratio of invested funds in digital transformation (RIFDT)	-	RIFDT = digital transformation budget/business turnover
	Ratio of the training hours of digital transformation (RTHDT)	-	RTHDT = training hours dedicated to the digital transformation/total training hours
Output	Digital transformation techniques (DTT)	Digital infrastructure	The integrity of data security, information systems and information services is high.
		Data value	The degree to which the company gathers, analyzes and applies information when making its business decisions is high.
	Organizational operations (OO)	Leadership consensus	The degree of consensus among company leadership regarding the vision and strategies of the digital transformation and the company's digital culture is high.
		Organizational capabilities	The degree of understanding and application of digital skills among the company's staff, in both digital transformation and other departments, is high.
		Ecosystems	The degree of information exchange and application between ecosystems is high. (Note: Ecosystems typically include multiple affiliate industries, and in a system, vendors not only work together but also engage in some degree of competition.)
	Process optimization (PO)	Internal process optimization	The degree to which the company's internal workflows (purchase orders, procurement, warehousing and interdepartmental collaborations) have been optimized and digitized is high.
		External process optimization	The degree to which the company's external workflows (supply chains, sales channels, marketing channels, customer service and after-sales support) have been optimized and digitized is high.

Table A1. *Cont.*

Variables/Dimensions	Indicators	Calculation/Question Statement
Customer experiences (CE)	Customer acquisition	The ability of the company to collect and analyze internal and external data to further understand customer patterns, demands and preferences is high.
Business models (BM)	Business model innovation	The ability of the company to develop innovative business models to open up new markets is high.

References

1. Tabrizi, B.; Lam, E.; Girard, K.; Irvin, V. Digital Transformation Is Not about Technology. *Harv. Bus. Rev.* **2019**, *13*, 54–73.
2. Evans, N.D. Assessing Your Organization's Digital Transformation Maturity. 2017. Available online: https://www.cio.com/article/3213194/assessing-your-organization-s-digitaltransformation-maturity.html (accessed on 15 March 2022).
3. Deloitte. Digital Maturity Model Achieving Digital Maturity to Drive Growth. 2018. Available online: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Technology-Media-Telecommunications/deloitte-digital-maturity-model.pdf (accessed on 23 February 2022).
4. Hess, T.; Benlian, A.; Matt, C.; Wlesbock, F. Options for Formulating a Digital Transformation Strategy. *MIS Q. Exec.* **2016**, *15*, 123–139. [CrossRef]
5. Bradley, C.; Hirt, M.; Smit, S. Eight shifts that will take your strategy into high gear. *The McKinsey Quarterly*, 11 June 2018; pp. 88–100.
6. Mitrović, Đ. Broadband adoption, digital divide, and the global economic competitiveness of Western Balkan countries. *Econ. Ann.* **2015**, *60*, 95–115. [CrossRef]
7. Kumar, S.; Russell, R.R. Technological change, technological catch-up, and capital deepening: Relative contributions to growth and convergence. *Am. Econ. Rev.* **2002**, *92*, 527–548. [CrossRef]
8. Chetty, K.; Qigui, L.; Gcora, N.; Josie, J.; Wenwei, L.; Fang, C. Bridging the digital divide: Measuring digital literacy. *Economics* **2018**, *12*, 1–20. [CrossRef]
9. Mehrabian, S.; Alirezaee, M.R.; Jahanshahloo, G.R. A complete efficiency ranking of decision making units in data envelopment analysis. *Comput. Optim. Appl.* **1999**, *14*, 261–266. [CrossRef]
10. Raab, R.; Kotamraju, P. The efficiency of the high-tech economy: Conventional development indexes versus a performance index. *J. Reg. Sci.* **2006**, *46*, 545–562. [CrossRef]
11. Ceccobelli, M.; Gitto, S.; Mancuso, P. ICT capital and labour productivity growth: A nonparametric analysis of 14 OECD countries. *Telecommun. Policy* **2012**, *36*, 282–292. [CrossRef]
12. Mitrovic, D. Measuring the efficiency of digital convergence. *Econ. Lett.* **2020**, *188*, 2–4. [CrossRef]
13. Magdalena, J.; Urbaniec, M. Development of Sustainability Competencies for the Labour Market: An Exploratory Qualitative Study. *Sustainability* **2019**, *11*, 5716. [CrossRef]
14. Patton, M.Q. *Qualitative Research and Evaluation Methods*, 4th ed.; Sage Publications, Inc.: London, UK, 2015.
15. Silverman, S.D. *Doing Practical Research: A Practical Handbook*; Sage Publications, Inc.: London, UK, 2005.
16. Charnes, A.; Cooper, W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
17. Tone, E.K. A Slack Based Measure of Efficiency in Data Envelopment Analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
18. Avkiran, N.; Tone, K.; Tsutsui, M. Bridging radial and non-radial measures of efficiency in DEA. *Ann. Oper. Res.* **2008**, *164*, 127–138. [CrossRef]
19. Farrell, M.J. The measurement of productive efficiency. *J. R. Stat. Soc. Ser. A* **1957**, *120*, 253–281. [CrossRef]
20. Banker, R.D.; Charnes, A.; Cooper, W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
21. Kane, G.C.; Palmer, D.; Phillips, A.N.; Kiron, D.; Buckley, N. *Strategy, Not Technology, Drives Digital Transformation*; MIT Sloan Management Review and Deloitte University Press: Cambridge, MA, USA, 2015.
22. Loonam, J.; Eaves, S.; Kumar, V.; Parry, G. Towards digital transformation: Lessons learned from traditional organization. *Strateg. Change* **2018**, *27*, 101–109. [CrossRef]
23. Bughin, J.; Manyika, J.; Catlin, T. *Twenty-Five Years of Digitization: Ten Insights into How to Play It Right*; McKinsey Global Institute: San Francisco, CA, USA, 2019.
24. OOSGA. Available online: https://global.oosga.com/solutions/tide/ (accessed on 16 March 2022).
25. Digital Transformation Toolkit. 2020. Available online: https://www.dpc.sa.gov.au/data/assets/pdf_file/0008/46565/Digital_Transformation_Toolkit_Guide.pdf (accessed on 5 March 2022).
26. Probst, L.; Lefebvre, V.; Martinez-Diaz, C.; Unlu Bohn, N.; PwC, D.; Klitou, J.C. *Digital Transformation Scoreboard 2018: EU Businesses Go Digital: Opportunities, Outcomes and Uptake*; European Commission: Luxembourg, 2018.

27. Salesforce.com Report, What Is Digital Transformation. 2021. Available online: https://www.salesforce.com/products/platform/what-is-digital-transformation/ (accessed on 18 March 2022).
28. Morakanyane, R.; Grace, A.; Philip, O. Conceptualizing digital transformation in business organizations: A systematic review of literature. In Proceedings of the 30th Bled eConference, Digital Transformation—From Connecting Things to Transforming Our Lives, Bled, Slovenia, 18–21 June 2017.
29. Tichert, R. Digital Transformation maturity: A systematic review of literature. *ACTA Univ. Agric. Silvic. Mendel. Bus.* **2019**, *67*, 1673–1687. [CrossRef]
30. Vial, G. Understanding Digital transformation: A review and a research agenda. *J. Strateg. Inf. Syst.* **2019**, *29*, 118–144. [CrossRef]
31. Saarikko, T.; Westergren, U.H.; Blomquist, T. The internet of things: Are you ready for what's coming? *Bus. Horiz.* **2017**, *60*, 667–676. [CrossRef]
32. SAP Report. 2017. Available online: https://www.sap.com/taiwan/cmp/dg/tw-digital-transformation-report/typ.html (accessed on 8 March 2022).
33. Graneheim, U.H.; Lundman, B. Qualitative content analysis in nursing research: Concepts, procedures and measures to achieve trustworthiness. *Nurse Educ. Today* **2004**, *24*, 105–112. [CrossRef]
34. Krueger, R.A. *Focus Groups: A Practical Guide for Applied Research*, 2nd ed.; Sage Publications, Inc.: Thousand Oaks, CA, USA, 1994.
35. Krueger, R.A.; Casey, M.A. *Focus Groups: A Practical Guide for Applied Research*, 3rd ed.; Sage Publications, Inc.: Thousand Oaks, CA, USA, 2000.
36. Gürbüz, T. Enabling Digital Transformation in Education and Training: Towards Effective Human Capital Development, Middle East Technical University, Turkey. In *Recent Developments in Individual and Organizational Adoption of ICTs*; IGI Global: Hershey, PA, USA, 2021.
37. Lefever, S.; Dal, M.; Matthiasdottir, A. Online data collection in academic research: Advantages and limitations. *Br. J. Educ. Technol.* **2007**, *38*, 574–582. [CrossRef]
38. Wright, B.; Schwager, P.H. Online survey research: Can response factors be improved? *J. Internet Commer.* **2008**, *7*, 253–269. [CrossRef]
39. Likert, R. A technique for the measurement of attitudes. *Arch. Psychol.* **1932**, *22*, 1–55.
40. Vega, M.; Pardo, R.; Barrado, E.; Debán, L. Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis. *Water Res.* **1998**, *32*, 3581–3592. [CrossRef]
41. Bughin, J.; Deakin, J.; O'Beirne, B. Digital Transformation: Improving the Odds of Success. *The McKinsey Quarterly*. 22 October 2019. Available online: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/digital-transformation-improving-the-odds-of-success (accessed on 18 August 2020).