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ORIGINAL RESEARCH ARTICLE

Principal component analysis and DEA: A combined measure

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ABSTRACT

The present study is focused on the integrated DEA method using principal component analysis (PCA) applied in the case of Indian Hotels and Restaurants. According to the given choice of the principle, several combinations of input-output principal components have been selected. The adopted method was applied to the data set of selected 45 Indian H&Rs and measured the performance of each H&R under each input-output PC combination. H&Rs are ranked based on the efficiencies and calculated a linear trend between the ranks obtained under each combination of input-output principal components. The top-ten H&Rs are identified and further applied to all the adopted methods on them. It is noticed that five H&Rs namely Royal Twinkle Star Club Pvt. Ltd., Classic Citi Invsts. Pvt. Ltd., Nehru Place Hotels Pvt. Ltd., Mcdonald's India Pvt. Ltd., and Sodexo Food Solutions India Pvt. Ltd., are the most efficient among the selected 45 H&Rs.

Keywords: hotel industry; restaurant; efficiency; data envelopment analysis; PCA; combined PCA-DEA; India

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1. Introduction

India has a vast hotel and restaurant sector. As India devastates the UK and France to transform into the fifth-greatest world economy with a GDP of $2.94 trillion, this sector has huge potential for advancement. This sector was surveyed to create $75 billion by 2021 from $46.5 billion out of 2016. Both facilitated and confused regions contribute in much the same way to business age and use around 7.3 million people beginning in 2018–2019[1].

India boasts a large hotel and restaurant industry. As India surpasses the United Kingdom and France to become the world's fifth-largest economy with a GDP of $2.94 trillion, this area has enormous economic potential. This sector is expected to grow to $75 billion in value by 2021, up from $46.5 billion in 2016[2]. Currently, the inbound tourism industry has ceased operations, with India placed under lockdown, visas suspended, and global travel advisories issued. The business of eating is almost certainly going to shift in the post-Covid-19 era. A portion of the acceptable projections in this area includes the end of social eating, the rise of premium conveyances, the beginning of home cooking, and a greater preference for healthier food. The only option to re-establish such a market following the Covid would be to increase domestic travel. This industry must devise quick and efficient methods for conveying quality to their clients to retain them.

As per Govt. of India, there are roughly 2 million road food sellers across India. This portion has stayed well known in the mass populace because of its reasonableness, taste, and accommodation. The quantity of Indians going inside India has expanded significantly since 1997, ascending from under 200 million to around 2 billion in 2019. Numerous components emphatically affect the travel industry, lodging, and eatery areas like regular development with an increment in two and four-wheelers, intense fall in homegrown air travel costs, rising per capita pay; expansion in utilization consumption particularly in youth, simplicity of booking administrations through the web; improvement in the quality and number of inns. As of late home conveyance and takeaway, administrations are expanding in notoriety because of its comfort. This is decreasing the continuous functional expenses of staff, utilities, and so forth of numerous cafés. To exploit the developing interest in online home conveyance, numerous administrators came into the outsider online conveyance administrations in India.

Hospitality is one of the key sectors in tourism, and the examination of proficiency is a fundamental part of this area. This study will attempt to examine the technical efficiencies of the Indian hotels and restaurant sector for the year 2019–2020, as a higher degree of efficiency is critical to the survival and growth of this sector in an intensely competitive environment, especially after the increase in digital or online payments. The paper aims to obtain the constant return to scale (CRS), variable return to scale-input oriented (VRS-IP), and variable return to scale-output oriented (VRS-OP) bias-corrected efficiency scores and ranks for H&Rs.

The paper unfolds as follows: Section 2 provides the outline of basic data envelopment analysis (DEA) models and literature review followed by a discussion on principal component analysis methodology using DEA in Section 3. A description of the data and variables used is provided in Section 4. Section 5 presents the results and discussion, followed by the conclusions in the last.

2. Literature review

The hotel industry is rich in literature that analyzes the performance in terms of efficiency of this industry. Most of the studies have used Classical ratio analysis and/or aggregate indices of market performance. Papers applying Stochastic Frontier Analysis (SFA) in this sector: The first paper applying stochastic translog production frontier in tourism was applied SFA in 42 Enatur hotels from 1999–2001[3,4]. He has taken sales and market share as output variables and operational cost as an input variable. The technical progress analyzed in the Portuguese hotel using the SFA method between 1998 and 2002[5]. The results show relatively low efficiency scores due to a high degree of resource underutilization. Some studies have analyzed the productivity of this sector[6–8].

Data envelopment analysis (DEA) appears to be fairly popular amongst recent researchers. The DEA was first applied in 60 fast-food restaurants[9]. They employ the model to provide efficient input and output targets for DMU managers. The efficiency indices of hotels in Portuguese was estimated in study of Assaf and Agbola[8]. The study identified peer groups and slacks for inefficient hotels. The DEA methodology is also used to select strategies that improve the performance of hotel companies[10,11]. The study analyzed different levels of efficiency, targets and slacks, and the identified efficient peers. A non-radial DEA model is also applied to evaluate the operational efficiency of tourist hotels in Taipei[12]. An exploratory study of marketing, physical, and people-related performance criteria in 333 hotels in the UK was done in Ramanathan[13]. Manasakis et al.[14] estimate the relative efficiency of 50 superior hotels in Crete. They identify inefficiency causes and suggest managerial implications to relevant business experts and managers to increase hotel efficiency. Wu et al.[15] reviewed recent studies published on tourism and hotel demand modeling and forecasting to identify emerging topics and methods for future research. The last few years have witnessed exhaustive work on efficiency measurement of the hotel industry throughout the world. Bernini and Guizzardi[16] evaluated the relevance of environmental factors on hotels' performance by applying the Meta frontier approach. Huang[17] analyzed the efficiency of manual and non-manual human resources for 67 tourist hotels in Taiwan by applying a hybrid DEA model. The study evaluated the inefficiency caused by radial inputs and it indicates that most of the hotels are efficient in their utilization of non-manual labor. Phucharoen and Sangkaew[18] highlighted the role of firm efficiency on internalization in Thailand's hotel industry through the DEA method in 1356 hotels located nationwide.

There is a dearth of studies on the performance of Indian hotels and restaurant companies. There are only a few studies in the Indian context in this sector. Sanjeev[19] applied DEA in this sector to measure the efficiency of 68 public Ltd. hotel and restaurant companies operating in India by applying basic DEA models. The study identified top performers and gave policy implications for managers in strategic and operational decisions to improve their efficiency scores and found a positive correlation between the efficiency scores and the size of the companies. Mahajan et al.[20] use DEA-based Principal Component Analysis (PCA) to Indian H&Rs for 2019–2020 to assess the efficiency and set targets for the inefficient one.

3. Methodology

The beginning of DEA in economic literature can be found in the early 1950s when Koopmans[21] defined technical efficiency as "an input-output vector is technically efficient if, and only if, increasing any output or decreasing any input is possible only by decreasing some other output or increasing some other input". This definition in economics is treated as a Pareto-Koopmans condition of technical efficiency. Farrell[22] extended the work of Koopmans and made a path-breaking contribution by constructing a linear programming (LP) model using actual input-output data of a sample of firms. The use of linear programming techniques of Farrell[22], eventually influenced Charnes et al.[23] to develop DEA.

The choice of DEA over its archrival SFA in the present context is directed by its intrinsic advantages such as it can handle multiple inputs and outputs easily in DEA; there is no need to specify any explicit functional form for the production function as DEA makes few assumptions about the form of technology and mathematical programming techniques that can be used to get pointwise estimates of the production function. This is a key advantage in light of the usual absence of such information. Third, DEA identifies the inefficiency in a particular DMU by comparing it to similar DMUs regarded as efficient rather than trying to associate a DMU's performance with statistical averages as it is done in SFA. Further, this approach helps to assess the reasons for inefficiency such as inefficiency due to scale or size (scale inefficiency) and/or management practices (pure technical inefficiency).

3.1. Selection of the model

In the basic CCR based on constant returns to scale (CRS) and BCC based on variable returns to scale (VRS) models the efficiency is measured either by changing inputs or by changing outputs, i.e., either the input-oriented model or output-oriented model. In an input-orientation model (input minimization) desired output is produced with minimum inputs. On the other hand, the output orientation model maximizes the outputs while the input is kept at a constant level. However, the radial CCR model[21], and BCC model[7] suffer from one shortcoming; they neglect the slacks in the evaluation of efficiencies. So, to overcome this shortcoming sometimes efficiency scores can be computed using a non-radial and non-oriented model known as the "slack-based model" given by Tone[24]. When both inputs and outputs can simultaneously be changed, i.e., the DMU can reduce inputs and augment outputs simultaneously, a non-oriented SBM model is used. This model allows managers to work on both inputs and outputs to achieve efficiency. Generally, in the case of hotels and restaurants, it is difficult to choose the orientation (input or output) for the evaluation of efficiencies. It is not admirable to reduce input levels or increase output levels regarding H&Rs. So, in this study, we use orientation independence of CCR, orientation-dependent BCC models, and also a non-oriented and non-radial model known as the SBM-DEA model. Mogha et al.[25] applied the SBM model to analyze the efficiencies of public-sector hospitals of Uttarakhand (India). Several studies have applied the output-oriented model and other input-oriented approaches. In this current article, Data Envelopment Analysis with Shannon's Entropy is being used to calculate the efficiency scores of the selected Hotels and Restaurants in India. The description of Shannon's Entropy with DEA is described in the next section.

3.2. Principal component analysis (PCA)

Experimentally handling huge data sets consisting of many features (variables) is tedious. A special emphasis is to be given to reducing the dimensionality of the given data set to find a set of new variables that have less cardinality compared to the set of original variables. Principal component analysis (PCA) is a technique of feature reduction and the set of new variables is known as principal components (PCs). They are uncorrelated and ordered according to the total information retained in them. The total information fraction is calculated using the concept of eigenvalues of the covariance matrix of the given data set matrix. The variables reduction should be done such that data loss is minimal when higher dimensions are dropped. For detailed PCA methodology, one can refer, to Bro and Smilde[26].

3.3. Principal component analysis (PCA)-DEA

Wang et al.[27] used the correlation method to select the input and output variables related to the Vietnamese agroforestry companies. Morita and Avkiran[28] proposed Mahalanobis distance and fractional factorial design methods for the selection of variables from a large number of possible combinations. Li et al.[29] proposed Akaike's information criteria rule to select the necessary variables from the given redundant data sets. A machine learning algorithm 'principal component analysis' (PCA) helps to select the necessary variables from the given large data sets. In the current study, we applied PCA to the input and output variables separately to reduce the number of variables and then applied a basic DEA method CRS. In the literature, it can be found that the joint PCA-DEA method has been employed in several fields[30–32]. For the present study, we adopted the joint PCA-DEA method given by Adler and Berechman[33]. The detailed operational procedure of PCA-CRS is depicted in **Figure 1**. It can be found in the literature that PCA-DEA is applied to hydrogel compositions with various combinations of principal components in the selection of the most efficient gels[34].

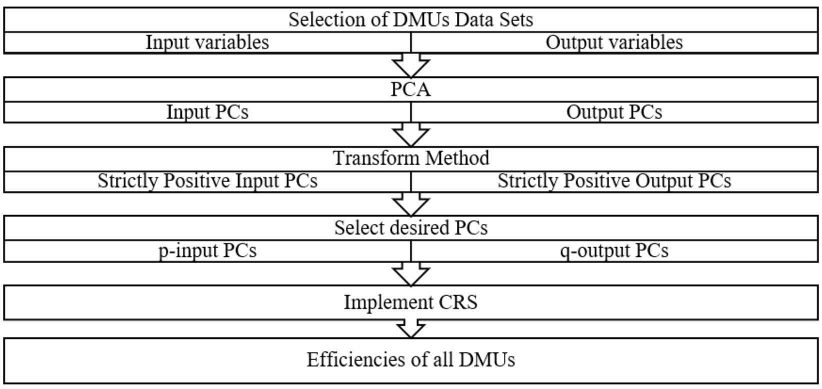

Figure 1. PCA-DEA methodology.

4. Description of data and variable construct

4.1. Description of data

The prowess database of the Centre for Monitoring Indian Economy (CMIE) provides data on a large number of manufacturing firms, including the hotel and restaurant sector. It is an online database provided by the CMIE and covers financial data for over 23,000 companies operating in India. Most of the companies covered in the database are listed on stock exchanges, and the financial data includes all the information that operating companies require to disclose in their annual reports.

According to the thumb rules that "the number of DMUs must be greater than the product of inputs and outputs" or "the number of DMUs should be at least three times the sum of input(s) and output(s) variables" is being opted for the selection of the DMUs. Therefore, the size of the sample is more than adequate according to the thumb rules of DEA literature[35,36].

To maintain the homogeneity of the DMUs, only 45 large-sized DMUs were selected in the study. The size of the company can be decided based on size, total assets, market value of equity, etc. We selected large H&R companies based on total assets. Many studies have used total assets to determine the size of the company. In case of a lack of data for some of the variables, we have to drop a few DMUs. Initially, we selected 50 H&Rs, then after running the model it was realized that 5 H&Rs were outliers, as some DEA models give efficiency results close to zero. This was practically not possible and therefore, we dropped these H&Rs from the selected set. Therefore, these H&Rs were excluded from the study, and finally, only 45 large private Ltd. H&R companies were selected.

4.2. Variable construct

In DEA literature it has been observed that there are some major concerns that to be taken care of. First, is the selection of input and output variables and second is the issue of measurement error addressed by scrutinizing data for outliers.

The selection of inputs and outputs of the model is a key part of DEA. The selection of inputs and outputs should be in such a way that obtained results give the best policy implication to the company.

The study uses the inputs and outputs based on the financial information available for the hotel and restaurant companies. The inputs considered are Capital employed, Current assets, and Operating costs. Capital employed includes shareholders' funds (common stock, preference stock, reserves) and long-term liabilities (debentures and long-term debt). Operating expenses include selling, general and administrative expenses, depreciation & amortization, and other operating expenses. The output variables are operating income and profit before depreciation, interest, and tax (PBDIT). Operating income is calculated by subtracting operating expenses from gross profit. DEA also has to meet the condition that all inputs have to be positive and positively related to at least one output. In our case, all the variables fulfill this requirement.

To provide a rational analytical basis for the selection of variables, a statistical analysis has been carried out. Descriptive statistics related to inputs and output are presented in **Table 1**. As it is evident, there appears to be a significant difference persisting among the Hotels and restaurants, as indicated by minimum and maximum values. The average total income per H&R is ₹1832.80 million with a standard deviation of ₹2601.35 million. The minimum total income is ₹80.20 million and the maximum is ₹14152.40 million, which displays the range in size of H&R in this sector. It is observed from **Table 1**, that the average of total expenses stands at ₹1908.02 million suggesting that the private Ltd. H&R sector has high fixed asset intensity and low operating cost intensity.

Table 1. Descriptive statistics of the input and output variables.

	Total capital	Net fixed assets	Current assets	Total expenses	Total income	PBDITA
Max	13,926.5	26,915.2	3187.2	13,935.8	14,152.4	1341.6
Min	7.8	0.1	41	17.1	80.2	30.1
Average	1562.88	4214.96	698.57	1908.02	1832.80	367.70
SD	2811.86	4499.49	746.00	2562.54	2572.28	370.59

5. Results and discussion

Our study focused on the applicability of a joint method principal component analysis and DEA to the 45 H&Rs of India. We used the basic CRS DEA method in the joint PCA-DEA method, and the results are shown in **Figures 2–5** and **Tables 1–4**. The PCA-DEA method is applied using a *p*-*q* combination of principal components (PCs) where *p* and *q* represent the selected *p* and *q*-number of input and output PCs respectively. **Table 2** represents the eigenvalues and their percentage of total variance of both input and output data. It helps in selecting new uncorrelated numbers of input and output variables with less loss of information. It admits to take *p* is 2 or 3 and *q* is 1 or 2. The value *q* is equal to 2 representing two output PCs allowing to test of the model with the given output data and is represented with *q* is equal to zero in a special case.

Table 2. Eigenvalues and their percentage of total variance for the 45 H&Rs input and output data.

Input eigenvalues	%	Output eigenvalues	%
23,269,666.8	64.50	6,805,758	98.53
6,698,795.45	83.07	101,718.2	100
5,738,207.5	98.97	-	-
370,130.86	100	-	-

The efficiency values obtained by the PCA-DEA using the original CRS method with 3-1, 3-2, and 3-0 PCs are shown in **Figure 2**. It is noticed that the number of efficient DMUs is less in PCA-DEA methods compared to the original CRS method. The DMUs H3, H9, H26, and H34 are efficient in CRS and all the combined PCA-DEA methods. However, the CRS-efficient DMUs H13, H17, H20, and H28 are inefficient in all the PCA-DEA methods. The CRS inefficient DMU H1 with 0.8291 efficiency became efficient in all the PCA-DEA methods. The CRS efficient DMU H15 is efficient in all PCA-DEA methods except for the 3-1 PCs method. It is clear from **Figure 2** that the efficiencies of 36 DMUs are bounded below by the efficiencies obtained using the 3-1 PCs method and bounded above by the efficiencies obtained using the original CRS method.

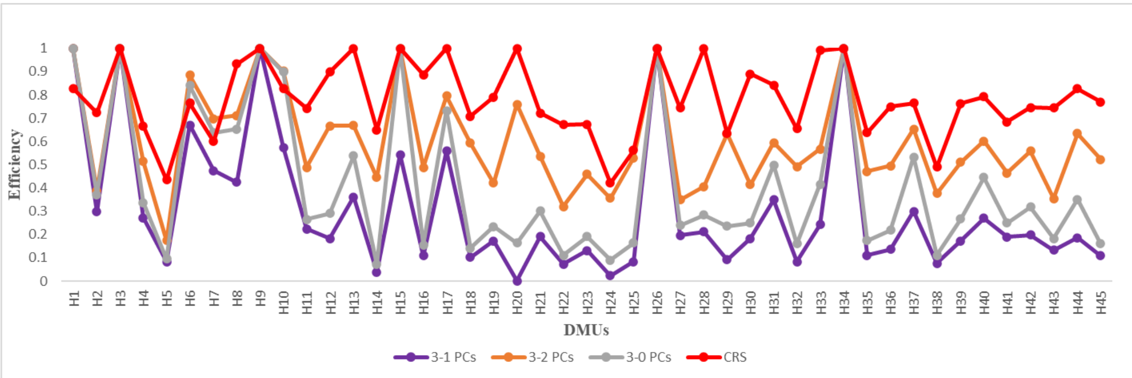

Figure 2. DEA and PCA-DEA results with 3-1, 3-2, and 3-0 PCs combinations using the CRS method.

Figure 3 shows the efficiencies of the 45 DMUs using original CRS, 4-1 PCs, 4-2 PCs, and 4-0 PCs combinations. Like the previous case of p is equal to 3, it is clear that efficiencies of 33 DMUs are bounded below by the efficiencies obtained using the 4-1 PCs method and bounded above by the efficiencies obtained using the original CRS method. The 3-1 PCs efficient DMUs are efficient in the 4-1 PCs method and 3-0 PCs efficient DMUs are efficient in the 4-0 PCs method. However, inefficient DMU H20 in the 3-2 PCs method is efficient in the 4-2 PCs method.

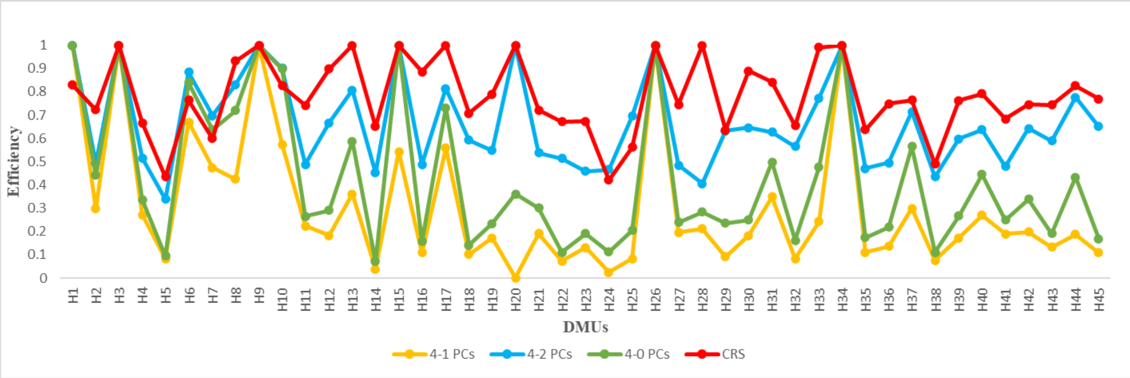

Figure 3. DEA and PCA-DEA result with 4-1, 4-2 and 4-0 PCs combinations using the CRS method.

From **Figures 2** and **3** it is clear that the number of efficient DMUs is almost equal in the respective $p = 3$ and $p = 4$ cases for various q values. It indicates attention to observing the efficiencies of all the DMUs. Hence, the DMUs have assigned ranks using the efficiencies obtained by all the adopted methods. The correlation between the ranks by all the adopted PCA-DEA methods is shown in **Table 3**. The methods that have a correlation of more than 0.95 have been considered and the efficiencies of all DMUs using those methods such as 3-1 PCs, 3-0 PCs, 4-1 PCs, and 4-0 PCs are depicted in **Figure 4**. It is noticed that the efficiencies of all DMUs obtained using 3-1 PCs are identical to the efficiencies obtained by the 4-1 PCs method. However, 32 DMUs have obtained identical efficiencies in 3-0 PCs and 4-0 PCs methods.

Table 3. Correlation between the ranks of efficiencies obtained by all the adopted PCA-DEA methods.

	3-1 PCs	3-2 PCs	3-0 PCs	4-1 PCs	4-2 PCs	4-0 PCs
3-1 PCs	1.0000	-	-	-	-	-
3-2 PCs	0.7124	1.0000	-	-	-	-
3-0 PCs	0.9684	0.8060	1.0000	-	-	-
4-1 PCs	1.0000	0.7124	0.9684	1.0000	-	-
4-2 PCs	0.6490	0.9087	0.7590	0.6490	1.0000	-
4-0 PCs	0.9275	0.8499	0.9814	0.9275	0.8268	1.0000

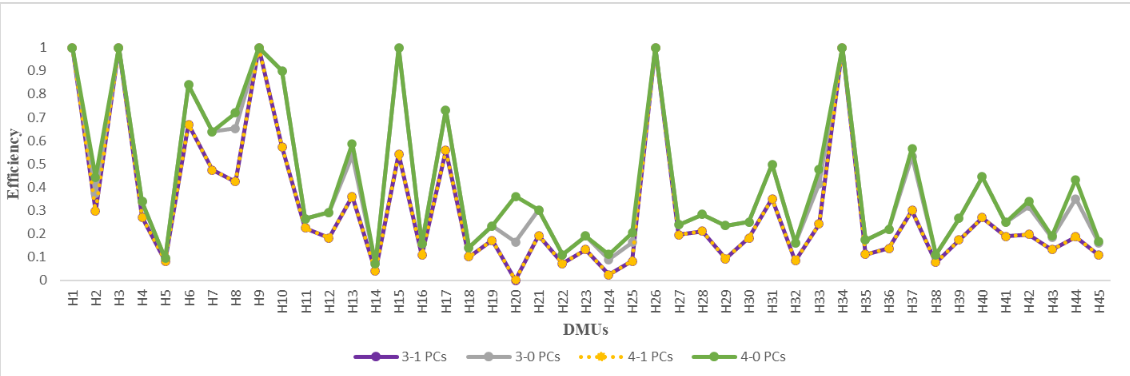

Figure 4. Comparison of efficiencies obtained using 3-1, 3-0, 4-1, and 4-0 PCs combinations.

Figure 4 and **Table 2** recommend observing the trend between the ranks obtained by the considered 3-0 PCs, 3-1 PCs, 4-0 PCs, and 4-1 PCs methods, and the results are illustrated in **Figure 5**. The R-squared value between 3-0 PCs & 3-1 PCs, and 4-0 PCs & 4-1 PCs are 0.9378 and 0.8602 respectively. The rankings are decidedly unswerving between 3-0 PCs & 4-0 PCs. The R-squared value between 3-1 PCs and 4-1 PCs is 1. **Figure 5** suggests using either 3-0 PCs or the 3-1 PCs method to calculate the efficiencies and rank the DMUs.

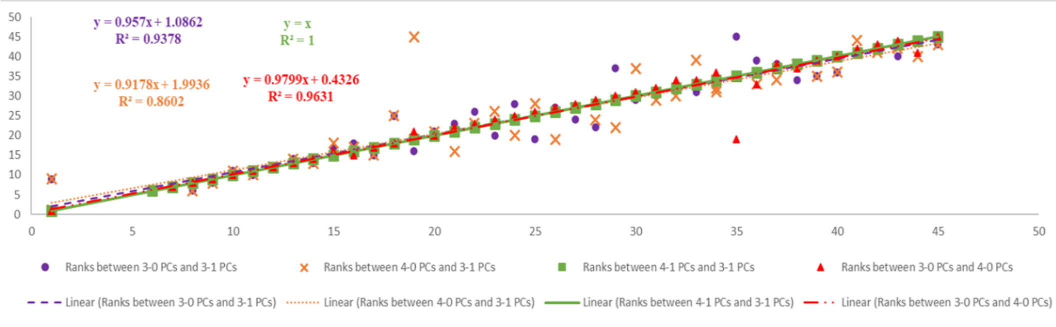

Figure 5. Scatter plot and linear fit between efficiencies of ranks obtained by various PCs.

Ten DMUs namely H1, H3, H9, H13, H15, H17, H20, H26, H28, and H34 are identified as efficient in any one of the methods including original CRS and all PCs combinations of PCA-DEA, and these are termed as top-ten DMUs. Eigenvalues and their percentage of total variance for the selected top-ten DMUs are shown in **Table 4**.

Table 4. Eigenvalues and their percentage of total variance for top-ten input and output data.

Input eigenvalues	%	Output eigenvalues	%
67,362,412.73	74.47	19,693,534.83	98.75
20,329,347.37	96.94	249,954.37	100
2,305,781.85	99.49	-	-
461,312.33	100	-	-

All the adopted methods have been applied to the selected top-ten DMUs and the results are shown in **Table 5**. It is clear from **Table 3** to choose a 3-1 PCs combination, and this method also satisfies the relation between the total number of variables and the number of DMUs to implement DEA methods on top-ten DMUs. Finally, using the 3-1 PCs method, it is found that the DMUs H3, H15, H26, H28, and H34 are overall efficient and which are CRS efficient as well.

Table 5. Efficiency values of the selected top-ten DMUs.

DMU	3-1 PCs	3-2 PCs	3-0 PCs	4-1 PCs	4-2 PCs	4-0 PCs	CRS
H1	0.9889	0.9889	0.9822	1	1	1	0.8291
H3	1	1	1	1	1	1	1
H9	0.8987	0.8987	0.8883	1	1	1	1
H13	0.8033	0.8033	0.8157	0.8169	0.8219	0.8406	1
H15	1	1	1	1	1	1	1
H17	0.9362	0.9362	0.9428	0.961	0.961	0.9703	1
H20	0.605	1	1	0.605	1	1	1
H26	1	1	1	1	1	1	1
H28	1	1	1	1	1	1	1
H34	1	1	1	1	1	1	1

6. Conclusion

The present study focused on the original CRS and joint principal component analysis (PCA)-DEA methods on the selected 45 hotels and restaurants in India. Principal components (PCs) for both input and output data have been calculated. In several combinations like 3, 4 PCs of inputs are combined with 0, 1, 2 PCs of outputs.

Based on the combinations, efficiencies are calculated and the efficiencies are ranked and hence, calculated the linear trend. Further, it was identified as a top-ten efficient DMUs and finally using 3-1 PCs combinations of the PCA-DEA method it is concluded that the DMUs H3, H15, H26, H28, and H34 are the overall efficient DMUs amongst the others.

7. Policy implications

In terms of policy development, cooperation between industry and government will assist facilities in charting a positive route. As most of the H&Rs are not operating efficiently and the pandemic has further increased their inefficiency, the government's role is critical for this sector's survival. The government should help this sector by enacting liberal legislation and supporting infrastructure programs. The hotel and tourism sector must quickly reassess its approach to professional development due to the fierce competition for skilled labor at all organizational levels. In this challenging time, providing opportunities for hotel workers to enhance their skill sets could help boost hotel company morale, as layoffs are a fact of life for both large and minor hotel companies. In this scenario, it will be beneficial for H&Rs to remain open for takeaway customers, as it will require fewer employees and the best alternative in this situation. To improve their efficiency, these companies must rethink their personnel needs by improving their workforce management capabilities. The government needs to extend more support to this sector by introducing a liberal legislation framework and supporting infrastructure policies.

Author contributions

Conceptualization, NS, SKM and RKPKP; methodology, RKPKP; software, RKPKP; validation, SKM and RKPKP; formal analysis, RKPKP; investigation, SKM; resources, SKM; data curation, SKM; writing—original draft preparation, NS; writing—review and editing, NS; visualization, RKPKP; supervision, SKM and RKPKP; project administration, SKM; funding acquisition, RKPKP. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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