

PURE TECHNICAL EFFICIENCY AND PERFORMANCE BENCHMARKING OF MALAYSIAN F&B FIRMS: A BCC- SBM ANALYSIS

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Abstract: *This study evaluates the relative revenue-generating resource efficiency of 14 publicly listed Malaysian food and beverage (F&B) companies using data envelopment analysis (DEA). Audited corporate data for financial years ending in 2025 were analysed using property, plant and equipment (PPE) and employee headcount as inputs, with revenue as the output. An input-oriented Banker–Charnes–Cooper (BCC) model under variable returns to scale was first employed to estimate radial pure technical efficiency. Peer-group analysis was subsequently conducted to identify the conditional benchmark prominence of frontier firms, followed by an input-oriented slack-based measure (SBM) to diagnose input-specific excesses among firms located below the radial frontier. Five companies achieved radial BCC scores of 1.000, while nine were below the frontier. Three-A Resources showed the highest conditional benchmark prominence under the reported optimal solutions. The SBM analysis identified the largest potential PPE reduction for Spritzer and the largest employee reduction for CAB Cakaran. The findings demonstrate that radial efficiency measurement and non-radial slack analysis provide complementary information on resource utilisation, with the latter revealing substantial differences in the sources of inefficiency across firms. The results are sample-specific and should therefore be interpreted as exploratory decision-support evidence rather than prescriptive resource-reduction targets.*

Keywords: *Data envelopment analysis; BCC model; slack-based measure; pure technical efficiency; benchmarking; food and beverage industry; resource efficiency*

Introduction

Malaysian food-processing firms transform capital and labour resources into marketable products while operating under differences in production scale, technology, product mix and resource intensity. These differences can generate substantial variation in the extent to which productive resources are converted into market outcomes. Previous studies involving food-related industries have consistently documented variation in technical and operational efficiency across firms and production units (Mohd Noor et al., 2016; Rodmanee & Huang, 2013; Tsai et al., 2022; Lee et al., 2025). Consequently, strong revenue performance alone should not be interpreted as evidence that productive resources are being used efficiently. A firm may generate substantial sales while employing comparatively high levels of productive assets or labour relative to other firms generating similar market output.

Conventional financial indicators such as profit margin, return on assets and revenue growth remain useful for evaluating specific dimensions of corporate performance. However, each indicator describes only a partial relationship and does not simultaneously assess how multiple productive resources are transformed into output (Cooper et al., 2011). Data envelopment analysis (DEA) addresses this limitation by constructing an empirical best-practice frontier from comparable decision-making units (DMUs). DEA is non-parametric, does not require a predefined functional form for the production process and permits multiple inputs and outputs to be incorporated within a unified efficiency framework (Charnes et al., 1978; Emrouznejad & Yang, 2018).

Recent applications continue to demonstrate the relevance of DEA in food-related industries. Tsai et al. (2022) employed DEA and the Malmquist productivity index to evaluate listed F&B firms in Vietnam and identified considerable differences in operational performance across firms and years. Sefeedpari et al. (2020) compared radial DEA and non-radial SBM in dairy production and showed that slack-sensitive analysis can provide additional information on

resource utilisation. More recently, Mavrommati et al. (2025) evaluated the operational and investment efficiency of dairy enterprises using personnel, net fixed assets and operating expenditure among the production inputs and revenues and gross profits among the outputs. Within Malaysia, Lee et al. (2025) similarly demonstrated the continuing relevance of technical-efficiency analysis in the food-processing industry. These studies indicate that resource-efficiency assessment remains important for understanding performance differences within food-related industries.

The original Charnes–Cooper–Rhodes (CCR) model assumes constant returns to scale, whereas the Banker–Charnes–Cooper (BCC) model permits variable returns to scale and isolates pure technical efficiency from scale-related effects (Banker et al., 1984). The BCC specification is appropriate for the present analysis because listed F&B firms can differ substantially in operational scale. An input orientation is adopted because the analytical question concerns the extent to which PPE and labour resources could be reduced while maintaining the observed level of revenue. Model orientation should correspond to the underlying managerial decision context rather than being selected solely for computational convenience (Cook et al., 2014).

Nevertheless, radial efficiency and input-specific slack represent different dimensions of resource inefficiency. The input-oriented BCC model identifies the maximum equiproportional contraction of inputs while preserving output, but such proportional contraction does not necessarily exhaust the potential improvement associated with individual inputs. Cova-Alonso et al. (2021) demonstrate that conventional CCR/BCC measures may leave non-zero input or output slacks after the proportional reduction path has been exhausted. Similarly, Bolós et al. (2023) distinguish classical radial efficiency measures from SBM, which directly incorporates slack information into efficiency assessment. The SBM developed by Tone (2001) therefore provides complementary diagnostic information rather than serving as a replacement for the BCC model.

Accordingly, this study has three objectives. First, it estimates radial pure technical efficiency using an input-oriented BCC model. Second, it examines the reported BCC reference sets to identify the conditional benchmark prominence of frontier firms. Third, it employs an input-oriented SBM to diagnose input-specific excesses and estimate improvement targets for firms located below the radial BCC frontier. The contribution of the study is therefore empirical and diagnostic rather than the development of a new DEA methodology. By linking radial efficiency assessment, peer identification and non-radial resource diagnosis, the analysis provides a structured assessment of revenue-generating resource efficiency among publicly listed Malaysian F&B firms.

Literature Review

DEA evaluates the relative efficiency of a set of comparable DMUs against a piecewise-linear frontier constructed from observed best-performing units. Its principal strength lies in the simultaneous treatment of multiple inputs and outputs without requiring distributional assumptions or a predetermined production function. However, DEA remains deterministic, and its results are conditional on the observations included in the analysis, the quality of the data, the variables selected and the specification of the model. Consequently, DEA efficiency should be interpreted as relative rather than absolute performance (Dyson et al., 2001; Thanassoulis et al., 2008).

The relationship between model dimensionality and sample size is particularly important. Charles et al. (2019) show that the inclusion of many performance measures relative to the

number of DMUs can weaken DEA's discriminatory power and result in a comparatively large number of units being classified as efficient. Khezrimotlagh et al. (2021) similarly demonstrate that discrimination and accuracy decline as the number of DMUs becomes smaller relative to the number of inputs and outputs. Conventional sample-size rules are therefore useful screening criteria, but satisfying such rules does not eliminate all concerns regarding discrimination. This consideration is particularly relevant when interpreting the proportion of efficient firms in relatively small empirical samples.

Comparability among DMUs is another fundamental requirement of DEA. Firms classified within the same broad industry may nevertheless differ in their technologies, product portfolios, vertical integration, outsourcing arrangements and resource-conversion processes. Mohsenirad and Triantis (2025) emphasise that DEA critically depends on the comparability of evaluated units and that technological heterogeneity may influence the estimated efficiency frontier. Accordingly, the interpretation of DEA results should recognise both the common production characteristics that permit benchmarking and the residual differences among firms that cannot be fully represented by a parsimonious input–output specification.

Capital and labour represent established productive resources in firm-level efficiency analysis. In the present study, PPE represents the productive asset base supporting operations, while employee headcount approximates labour utilisation. Revenue represents the monetary value generated from ordinary operating activities. Recent empirical applications provide support for comparable specifications. Erena et al. (2021) employed total fixed assets and employee numbers as inputs in an analysis of manufacturing efficiency, with value-added, operating surplus and sales-related measures used as outputs. Mavrommati et al. (2025) used personnel, net fixed assets and operating expenditure as production inputs and revenues and gross profits as outputs when evaluating dairy enterprises. Makkar and Illiyan (2026) similarly modelled labour and capital among the productive inputs and net sales revenue as the output when examining efficiency among Indian sugar companies. These studies support the use of fixed productive assets and labour as resource measures and revenue or sales as market-based outputs in firm-level DEA.

The use of revenue as an output nevertheless requires careful interpretation. Revenue is monetary rather than physical and may reflect differences in product prices, brand strength, product mix and market positioning. PPE can also reflect acquisition timing, depreciation practices and accounting policies, while employee headcount may be affected by outsourcing and vertical integration. Furthermore, a specification based on PPE, employees and revenue excludes other potentially important production factors and outcomes, including materials, energy, labour costs, profitability, product quality and environmental performance. The resulting frontier should therefore be interpreted specifically as revenue-generating resource efficiency rather than total corporate efficiency.

DEA has been widely applied in food and related industries. Rodmanee and Huang (2013) evaluated F&B companies using a two-stage DEA structure, while Mohd Noor et al. (2016) examined efficiency within the Malaysian halal processed-food industry. Ajija et al. (2018) investigated efficiency in food and beverage industrial production using DEA and stochastic frontier analysis, whereas Machmud et al. (2019) applied DEA to the Indonesian food industry. Náglová and Šimpachová Pechrová (2021) subsequently examined technical efficiency and its determinants in the food and drink industry. More recently, Tsai et al. (2022) evaluated the performance and productivity of listed Vietnamese F&B firms, while Lee et al. (2025) examined predictors of technical efficiency within the Malaysian food-processing industry.

Collectively, these studies demonstrate persistent variation in efficiency across food-related firms and provide a basis for further resource-efficiency benchmarking.

Although radial DEA models provide an interpretable overall measure of technical efficiency, they do not necessarily identify the complete structure of inefficiency. In an input-oriented radial model, all inputs are contracted by the same proportion until the radial frontier is reached. An individual input may nevertheless contain additional excess beyond the proportional contraction. Cova-Alonso et al. (2021) identify this as an important limitation of conventional CCR/BCC efficiency measures because non-zero slacks can remain after the proportional reduction path is exhausted.

SBM addresses this issue by incorporating slack directly into efficiency measurement. Tone (2001) developed SBM as a non-radial DEA measure that evaluates inefficiency through individual input and output slacks. Bolós et al. (2023) similarly characterise SBM as a non-radial approach that differs from classical radial efficiency models by explicitly incorporating slack into efficiency scores. In an applied food-production context, Sefeedpari et al. (2020) compared radial DEA with non-radial SBM and demonstrated that the two approaches provide different information regarding resource efficiency.

This distinction establishes the rationale for the sequential framework used in the present study. The BCC model remains the principal model for estimating radial pure technical efficiency under variable returns to scale. Peer analysis subsequently uses the BCC intensity structure to identify observed frontier firms contributing to reference combinations. SBM then provides a more detailed diagnosis of input-specific resource excess among firms identified below the radial frontier. BCC and SBM are therefore treated as complementary rather than competing models: the former answers the proportional resource-efficiency question, whereas the latter identifies the individual inputs responsible for additional resource gaps.

Methodology

Research Design, DMUs and Model Variables

This study adopts a cross-sectional DEA design using audited annual reports, financial statements and related corporate disclosures. Fourteen publicly listed Malaysian F&B companies with complete data for financial years ending in 2025 were retained as DMUs. PPE and revenue were expressed in RM million, while labour was represented by group-level employee headcount.

A conventional DEA rule of thumb suggested by Cooper et al. (2011) requires the number of DMUs to satisfy:

$$n \geq \max\{m, s, 3(m + s)\} \quad (1)$$

where n represents the number of DMUs, m represents the number of inputs and s represents the number of outputs. The present model contains two inputs and one output. Accordingly,

$$n \geq \max\{2, (1)3(2 + 1)\} = 9.$$

The sample of 14 DMUs therefore exceeds the conventional minimum requirement for the selected model specification. Nevertheless, compliance with this rule should not be interpreted as eliminating all concerns regarding discriminatory power, particularly in relatively small

DEA samples (Charles et al., 2019; Khezrimotlagh et al., 2021). The variables incorporated into the model are summarised in Table 1.

Table 1: Model Variables

Role	Variable	Operational Definition	Unit
Input 1	Property, Plant and Equipment (PPE)	Net carrying amount of group operating assets	RM million
Input 2	Employees	Group-level employee headcount	Headcount
Output	Revenue	Income from ordinary operating activities	RM million

The specification represents a parsimonious capital–labour–output structure. PPE approximates the productive asset base available to the firm, employee headcount represents labour resources and revenue captures market value generated from operations. Comparable firm-level studies have employed fixed assets or capital and employee or labour measures as productive inputs against revenue, sales or related market outputs (Erena et al., 2021; Mavrommati et al., 2025; Makkar & Illiyan, 2026).

Input-Oriented BCC Model

The first stage estimates radial pure technical efficiency using the input-oriented BCC model. For each evaluated firm o , the model identifies the maximum feasible proportional contraction of its inputs while maintaining at least the observed output level:

$$\min_{\theta, \lambda} \theta \quad (2)$$

subject to

$$\sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{io}, \quad i = 1, \dots, m, \quad (3)$$

$$\sum_{j=1}^n \lambda_j y_{rj} \geq y_{ro}, \quad r = 1, \dots, s, \quad (4)$$

$$\sum_{j=1}^n \lambda_j = 1, \quad (5)$$

$$\lambda_j \geq 0, \quad j = 1, \dots, n. \quad (6)$$

In Equations (2)–(6), x_{ij} denotes the quantity of input i used by DMU j , y_{rj} denotes the quantity of output r generated by DMU j , x_{io} and y_{ro} denote the observed inputs and output of the DMU under evaluation, and λ_j represents the intensity assigned to reference DMU j . The parameters m , s and n denote the number of inputs, outputs and DMUs, respectively. The variable θ represents radial input efficiency. The convexity restriction in Equation (5) imposes the variable-returns-to-scale condition that distinguishes the BCC model from the constant-returns-to-scale CCR specification.

A value of $\theta < 1$ indicates that the evaluated firm could proportionally contract its observed inputs while maintaining at least the existing level of revenue. Conversely, $\theta = 1$ indicates radial BCC efficiency. However, a radial score of unity does not automatically establish full Pareto efficiency because additional non-zero slacks may remain (Cova-Alonso et al., 2021).

The term radial pure technical efficiency is therefore used throughout the study. Scale efficiency is not estimated because a corresponding constant-returns-to-scale model lies outside the scope of the present analysis.

Peer Group Analysis

The second stage examines the reference structure generated by the BCC model. For each DMU with $\theta < 1$, a frontier firm enters the reported reference set when its optimal BCC intensity satisfies $\lambda_j > 0$. Reference frequency is defined as the number of below-frontier DMUs for which a particular efficient firm appears with a positive intensity value.

To provide additional information beyond reference frequency, cumulative positive intensity for benchmark j is expressed as:

$$C_j = \sum_{o \in I} \lambda_{jo}^+ \quad (7)$$

where I represents the set of below-frontier DMUs and λ_{jo}^+ represents a positive BCC intensity assigned to benchmark j when DMU o is evaluated.

Cumulative lambda therefore represents the aggregate positive reference weight assigned to a frontier firm across the reported optimal solutions. A larger cumulative value indicates that the benchmark contributes a greater aggregate weight to the convex reference combinations constructed for below-frontier firms. It does not represent another measure of efficiency and should not be interpreted as evidence that one frontier firm is intrinsically more efficient than another.

DEA models may admit alternative optimal intensity solutions. Consequently, reference sets and individual lambda values may not always be unique. The resulting reference frequency and cumulative lambda measures are therefore interpreted as conditional benchmark prominence under the reported optimal solutions, rather than as a definitive ranking of frontier firms (Rezaeiani & Ferooghi, 2018).

Input-Oriented SBM Model

The third stage applies an input-oriented SBM to firms identified below the BCC frontier. The analytical purpose of SBM differs from that of the preceding BCC model. BCC measures radial efficiency through an equiproportional contraction of all inputs, whereas SBM directly evaluates input-specific slack. A firm may therefore be relatively close to the BCC frontier while still exhibiting substantial excess in one particular resource. The SBM is used to identify these resource-specific patterns rather than to replace the radial BCC assessment.

Following Tone (2001), the input-oriented SBM for evaluated DMU o is formulated as:

$$\min \rho_I = 1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}} \quad (8)$$

subject to

$$\sum_{j=1}^n \lambda_j x_{ij} + s_i^- = x_{io}, \quad i = 1, \dots, m, \quad (9)$$

$$\sum_{j=1}^n \lambda_j y_{rj} \geq y_{ro}, \quad r = 1, \dots, s, \quad (10)$$

$$\sum_{j=1}^n \lambda_j = 1, \quad \lambda_j \geq 0, \quad s_i^- \geq 0. \quad (11)$$

In Equations (8)–(11), ρ_i denotes the input-oriented SBM score and s_i^- represents the excess associated with input i . The remaining notation follows that defined for the BCC model. The convexity restriction retains the variable-returns-to-scale assumption used in the primary BCC analysis.

The SBM analysis is applied to the nine DMUs previously identified as below the radial BCC frontier because the purpose of this stage is to diagnose the source and magnitude of resource excess and derive input-specific improvement targets. SBM is therefore employed as a complementary diagnostic procedure rather than as a substitute for the BCC model. The five firms with $\theta = 1$ are consequently described only as radially BCC-efficient; no claim of full Pareto efficiency is made. Verification of full Pareto efficiency would require explicit consideration of all remaining input and output slacks and is beyond the input-oriented diagnostic scope adopted in the present study. All models were solved separately using LINGO 22.0.

Results and Discussion

BCC Pure Technical Efficiency Results

The BCC scores obtained from Equations (2)–(6) are presented in Table 2. Five companies, representing 35.71% of the sample, obtained a radial BCC score of 1.000: Nestlé (Malaysia), Apollo Food Holdings, Hup Seng Industries, Three-A Resources and MSM Malaysia Holdings. The remaining nine companies, representing 64.29% of the sample, recorded scores below 1.000.

Among the below-frontier firms, CCK Consolidated recorded the highest BCC score at 0.967, indicating that it was closest to the radial frontier. Its score implies approximately 3.35% proportional input-contraction potential before consideration of additional input-specific slack. Ajinomoto followed with a score of 0.922. At the other end of the distribution, Farm Fresh recorded the lowest BCC score at 0.525, followed by Spritzer at 0.544 and SDS Group at 0.589.

Table 2: Input-Oriented BCC Scores

DMU	Company	BCC Score
1	Nestlé (Malaysia)	1.000
2	Ajinomoto (Malaysia)	0.922
3	Apollo Food Holdings	1.000
4	CAB Cakaran	0.826
5	Farm Fresh	0.525
6	Fraser & Neave Holdings	0.824
7	Hup Seng Industries	1.000
8	Kawan Food	0.744

9	Power Root	0.764
10	SDS Group	0.589
11	Spritzer	0.544
12	Three-A Resources	1.000
13	CCK Consolidated	0.967
14	MSM Malaysia Holdings	1.000

The proportion of firms located on the frontier requires cautious interpretation. Although the sample exceeds the conventional minimum indicated by Equation (1), the discriminatory power of DEA is influenced by the relationship between the number of observations and the number of performance measures. Charles et al. (2019) and Khezrimotlagh et al. (2021) demonstrate that smaller samples relative to model dimensionality can weaken discrimination and increase the proportion of DMUs appearing efficient. Consequently, the five firms with scores of 1.000 should not be interpreted as evidence that approximately one-third of the wider Malaysian F&B industry is universally efficient. Their frontier status is relative to the 14 firms, the selected financial year and the particular PPE–employee–revenue specification.

The results nevertheless demonstrate considerable variation in revenue-generating resource efficiency across the observed firms. This pattern is consistent with previous food-industry studies reporting heterogeneous technical efficiency arising from differences in firm size, production structure and resource utilisation (Ajija et al., 2018; Machmud et al., 2019; Náglová & Šimpachová Pechrová, 2021; Tsai et al., 2022; Lee et al., 2025). The BCC results therefore provide an initial radial assessment of how firms compare in converting capital and labour resources into revenue under variable returns to scale.

Peer Group Results

Table 3 reports the conditional benchmark prominence derived from the BCC intensity values. Reference frequency indicates the number of below-frontier firms for which an efficient company appears with a positive lambda value, whereas cumulative lambda calculated using Equation (7) represents the sum of those positive intensity values across the reported solutions. Three-A Resources and MSM Malaysia Holdings each appeared in five reference sets. Three-A Resources, however, recorded a cumulative lambda of 3.144 compared with 0.796 for MSM Malaysia Holdings. Apollo Food Holdings appeared in four reference sets with a cumulative lambda of 2.014, whereas Hup Seng Industries and Nestlé (Malaysia) each appeared in three reference sets.

Table 3: Conditional Benchmark Prominence

Conditional Rank	Efficient Benchmark	Reference Frequency	Cumulative Lambda
1	Three-A Resources	5	3.144
2	MSM Malaysia Holdings	5	0.796
3	Apollo Food Holdings	4	2.014
4	Hup Seng Industries	3	2.096
5	Nestlé (Malaysia)	3	0.951

The cumulative lambda values provide information about the contribution of individual frontier firms to the construction of reference combinations. The relatively large value for Three-A Resources indicates that it received a larger aggregate positive weight across the reported benchmark combinations for below-frontier firms. This does not imply that Three-A Resources has an efficiency score higher than the other frontier firms, because all five firms have the same

radial BCC score of 1.000. Instead, the value reflects its greater aggregate involvement in constructing the reference targets generated by the particular set of optimal BCC solutions.

This distinction is important because peer prominence and efficiency are conceptually different. An efficient firm may appear frequently as a benchmark because its observed input–output configuration is particularly relevant to several below-frontier firms, while another efficient firm may receive less reference weight despite also lying on the frontier. Furthermore, alternative optimal DEA solutions may generate different lambda values or reference combinations. The ordering in Table 3 should therefore be regarded as conditional benchmark prominence under the reported LINGO solutions rather than as a unique or globally robust ranking of the frontier firms.

SBM Results and Improvement Targets

The input-oriented SBM results obtained from Equations (8)–(11) are presented in Table 4. All nine firms identified below the radial BCC frontier obtained SBM scores below 1.000, confirming the presence of input-specific excess within this subsample. Because SBM incorporates non-radial input slack, its scores and improvement targets need not preserve the proportional reductions implied by the BCC model.

Table 4: Input-Oriented SBM Scores and Improvement Targets

Company	SBM Score	Target PPE	PPE Reduction (%)	Target Employees	Employee Reduction (%)
Ajinomoto	0.705	221.5848	51.24	616	7.84
CAB Cakaran	0.533	583.9871	15.72	1,041	77.75
Farm Fresh	0.520	290.7676	43.37	683	52.61
Fraser & Neave	0.709	1,317.6900	40.67	3,164	17.60
Kawan Food	0.631	75.6029	57.02	724	16.69
Power Root	0.744	103.6584	34.48	742	16.78
SDS Group	0.525	87.5675	34.33	732	60.63
Spritzer	0.467	215.1370	60.95	609	45.65
CCK Consolidated	0.675	257.7978	0.00	1,073	65.08

Power Root recorded the highest SBM score among the below-frontier firms at 0.744, followed by Fraser & Neave at 0.709 and Ajinomoto at 0.705. Spritzer recorded the lowest SBM score at 0.467. The ordering differs from that generated by the BCC model because the two measures represent different aspects of inefficiency. BCC measures proportional radial contraction, whereas SBM explicitly incorporates input-specific excess.

The result for CCK Consolidated illustrates this distinction particularly clearly. CCK was closest to the BCC frontier, recording a radial score of 0.967, yet its SBM score was substantially lower at 0.675. The SBM solution identified no excess PPE but indicated a 65.08% employee-related reduction target. Thus, CCK's radial distance to the frontier was relatively small, while its remaining resource gap under the selected non-radial model was concentrated in labour. This example demonstrates why the SBM phase provides information that cannot be inferred solely from the BCC score.

The resource-specific targets also reveal substantially different operational profiles among firms. Spritzer recorded the largest potential PPE reduction at 60.95%, followed by Kawan Food at 57.02% and Ajinomoto at 51.24%. These results indicate comparatively high asset

utilisation requirements relative to the observed reference combinations capable of maintaining the same revenue level. Conversely, CAB Cakaran recorded the largest employee-related reduction target at 77.75%, followed by CCK Consolidated at 65.08% and SDS Group at 60.63%. Ajinomoto exhibited the smallest employee adjustment at 7.84% despite having a considerably larger PPE adjustment. Firms displaying similar broad efficiency positions may therefore face very different sources of resource inefficiency.

The managerial interpretation of high PPE slack should focus initially on the utilisation of productive capacity rather than on immediate asset disposal. Firms with comparatively high PPE excess may examine equipment utilisation, production scheduling, idle or underused capacity, the redeployment of assets across operations and the timing of future capital expenditure. In some cases, asset-sharing or leasing arrangements may also provide opportunities to improve utilisation. However, retained capacity may support seasonal demand, maintenance requirements, anticipated expansion or product diversification. A DEA target should therefore initiate further operational investigation rather than serve as a direct instruction to dispose of productive assets.

Employee-related slack requires a different managerial response. Large employee targets should not be interpreted as direct recommendations for workforce retrenchment. Managers may first investigate workload distribution, production scheduling, process configuration and employee deployment. Opportunities for multiskilling, training, workflow redesign, technology adoption and redeployment to activities with additional capacity requirements may improve labour utilisation without requiring proportional workforce reductions. Where adjustment is operationally justified, gradual mechanisms such as natural attrition may be more appropriate than treating the numerical DEA projection as an immediate headcount-reduction requirement. The interpretation of SBM targets should also recognise the characteristics of the underlying accounting and operational data. PPE values are influenced by depreciation, acquisition timing and accounting policy, while group-level employee headcount may reflect differences in vertical integration, outsourcing and product diversity. The targets are therefore frontier-based diagnostic and planning signals rather than forecasts or automatic prescriptions. Operational feasibility, financial considerations, product quality, strategic capacity, employee welfare and sustainability should be considered before translating the estimated resource gaps into managerial action.

Taken together, the BCC and SBM results demonstrate the complementary nature of radial and non-radial efficiency assessment. The BCC model establishes the relative proportional efficiency position of each firm under variable returns to scale, while the subsequent SBM analysis reveals whether the diagnosed resource gap is concentrated in PPE, labour or both. The sequential use of the two models therefore provides a more informative diagnostic assessment than either the radial score or slack targets would provide in isolation.

Conclusion and Implications

This study evaluated the relative revenue-generating resource efficiency of 14 publicly listed Malaysian F&B companies using a sequential DEA framework comprising an input-oriented BCC model, conditional peer-group analysis and an input-oriented SBM. PPE and employee headcount were treated as productive inputs and revenue as the output. The BCC model identified five firms—Nestlé (Malaysia), Apollo Food Holdings, Hup Seng Industries, Three-A Resources and MSM Malaysia Holdings—on the radial frontier, while the remaining nine firms exhibited varying degrees of proportional input-contraction potential.

Peer-group analysis provided additional information on the role of frontier firms as observed benchmarks. Under the reported optimal BCC solutions, Three-A Resources and MSM Malaysia Holdings each appeared in five reference sets, with Three-A Resources recording the larger cumulative lambda. This result indicates greater aggregate participation by Three-A Resources in the convex reference combinations generated for below-frontier firms. Because reference sets may be non-unique, however, this finding represents conditional benchmark prominence rather than an absolute ranking of efficient companies.

The SBM results further demonstrated that radial proximity to the frontier does not necessarily imply limited input-specific inefficiency. Power Root recorded the highest SBM score among the below-frontier firms, while Spritzer recorded the lowest. Spritzer exhibited the largest PPE reduction target, CAB Cakaran the largest employee-related target and CCK Consolidated displayed a particularly distinct pattern in which no PPE excess was identified but substantial labour-related excess remained. These differences reinforce the value of analysing the composition of inefficiency rather than relying exclusively on an aggregate radial score.

From a managerial perspective, the findings suggest that efficiency improvement should be resource-specific. Firms characterised by substantial PPE slack may benefit from closer examination of capacity utilisation, production scheduling and capital deployment, whereas firms displaying substantial employee slack may require attention to workload allocation, process configuration, training and employee redeployment. Importantly, the numerical DEA targets are not intended to prescribe immediate asset disposal or workforce reductions. They identify resource configurations associated with the observed sample frontier and should therefore be used as starting points for more detailed operational assessment.

Methodologically, the findings also clarify the respective roles of the BCC and SBM models. The BCC model remains appropriate for measuring radial pure technical efficiency under variable returns to scale, while SBM provides complementary information regarding non-proportional input excess. Their sequential use does not imply that one model replaces or corrects the other. Instead, each addresses a different aspect of resource efficiency, allowing the study to distinguish overall proportional inefficiency from the resource-specific structure underlying that inefficiency.

Overall, the study provides an empirical benchmarking perspective on the utilisation of capital and labour among Malaysian listed F&B firms. The results should be interpreted as relative to the observed firms, financial year and selected model variables. Within these boundaries, the analysis offers a structured basis for identifying benchmark relationships and directing managerial attention towards the resource categories in which improvement opportunities appear most pronounced.

Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the study is restricted to 14 publicly listed Malaysian F&B firms and a single financial year. DEA constructs a frontier from the observations included in the analysis; consequently, the resulting scores are sample-specific and cannot be generalised directly to the wider Malaysian F&B industry. Although the 14-DMU sample satisfies the conventional rule of thumb adopted in Equation (1), relatively small DEA samples may still exhibit limited discriminatory power and a comparatively large proportion of frontier units (Charles et al., 2019; Khezrimotlagh et al., 2021).

Second, differences in product mix, vertical integration, outsourcing practices, reporting periods and business models may affect comparability among the evaluated firms. DEA relies on sufficient homogeneity among DMUs, and recent methodological research emphasises that unrecognised heterogeneity can influence estimated efficiency frontiers (Mohsenirad & Triantis, 2025). The results should therefore be interpreted within the broad common production context represented by the selected firms rather than as evidence of identical underlying production technologies.

Third, the input–output specification is deliberately parsimonious. PPE and employee headcount represent capital and labour resources, while revenue represents market output. The model does not explicitly incorporate materials, energy, labour cost, profitability, product quality or environmental performance. Revenue itself may also reflect pricing, inflation, brand strength and product mix. Accordingly, the estimated scores represent revenue-generating resource efficiency and should not be interpreted as comprehensive measures of overall corporate performance.

Fourth, the SBM analysis is applied to the nine firms identified below the radial BCC frontier because its role in the present study is to diagnose resource-specific excess and produce improvement targets for these firms. The five firms with BCC scores of 1.000 were not subjected to a separate zero-slack verification. Their status should therefore be interpreted specifically as radial BCC efficiency, rather than as confirmed full Pareto efficiency.

Future research could extend the analysis using larger and more comparable samples and multiple financial years. Alternative variable specifications could be examined to assess the sensitivity of the frontier to different representations of capital, labour, cost and market outcomes. Further studies may also explicitly verify strong efficiency among radial frontier firms and incorporate CCR–BCC comparisons to separate pure technical and scale efficiency. Bootstrap procedures could be employed to examine sampling sensitivity, while productivity-change approaches such as the Malmquist index could provide a longitudinal assessment of efficiency and technological change (Simar & Wilson, 1998).

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