

# PERFORMANCE EFFICIENCY OF SOCIAL MEDIA DIGITAL MARKETING PLATFORMS IN MALAYSIA USING CCR INPUT-ORIENTED DEA, CROSS EFFICIENCY, AND SBM MODELS

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**Abstract:** *Digital marketing platforms have become important channels through which organisations engage audiences and generate commercial value. This study evaluates the relative performance efficiency of eleven prominent social media digital marketing platforms in Malaysia using three Data Envelopment Analysis (DEA) approaches: the CCR input-oriented model, Cross Efficiency, and the Slack-Based Measure (SBM) model. The analysis considers three inputs—number of users, number of employees, and total expenses—and two outputs—potential advertising reach and total annual revenue. The CCR input-oriented model was first applied to identify relatively efficient and inefficient platforms. Seven platforms were found to be CCR-efficient, while Telegram, Twitter, LinkedIn, and Snapchat were identified as inefficient. Cross Efficiency was subsequently employed to discriminate among the CCR-efficient platforms, with YouTube obtaining the highest cross-efficiency score, followed by TikTok. The SBM model was then applied to further assess the four CCR-inefficient platforms by considering input excesses and output shortfalls. Overall, the findings demonstrate differences in the ability of social media platforms to utilise their existing audience base and operational resources to generate advertising reach and revenue. The study provides a relative*

*benchmarking perspective that may assist decision-makers in evaluating resource utilisation and platform performance within the digital marketing environment*

**Keywords:** *Data Envelopment Analysis (DEA); CCR input-oriented model; Cross Efficiency; Slack-Based Measure (SBM); social media platforms; digital marketing efficiency*

## Introduction

Marketing is a crucial aspect of business operations and continues to evolve in response to technological development and changing consumer behaviour. Traditional marketing commonly relies on channels such as television, radio, billboards, and print advertising, whereas technological advancement has expanded marketing activities into digital environments. Digital marketing encompasses a range of marketing techniques and technological tools used to reach consumers online and enables organisations to communicate with targeted audiences and develop their brand identities (Bala & Verma, 2018; Gustavsen, 2021). Within this environment, social media platforms have become particularly important because they facilitate continuous interaction among organisations, consumers, and online communities.

Malaysia has experienced substantial transformation in its digital environment. Early initiatives such as the Multimedia Super Corridor (MSC Malaysia) were developed to stimulate the growth of information and communication technology and contribute to the country's digital development (Injau, 2011). The subsequent expansion of internet access, digital communication, and social media has changed how organisations communicate with customers and conduct marketing activities. Digital platforms now provide businesses with opportunities to reach large audiences, communicate directly with consumers, and generate commercial value. However, differences in platform size, resources, advertising reach, and financial performance make direct comparison difficult. Consequently, platform selection should not depend solely on popularity or the absolute size of the user community but should also consider how efficiently available resources are converted into meaningful marketing and financial outcomes.

Data Envelopment Analysis (DEA) provides an appropriate framework for such an assessment because it evaluates the relative efficiency of comparable decision-making units (DMUs) involving multiple inputs and outputs simultaneously (Charnes et al., 1978; Martić et al., 2009). DEA has been applied in studies involving internet companies, online social networks, social media, telecommunications, and digital marketing (Serrano-Cinca et al., 2005; Martínez-Núñez & Pérez-Aguilar, 2014; Kotnisa & Guzowska, 2021; Ishaq & Ajibesin, 2022). Such applications demonstrate the usefulness of DEA when organisational performance cannot be adequately represented by a single financial, operational, or engagement indicator.

An important consideration in DEA is the specification of the production process and the classification of variables as inputs and outputs. Variable classification should reflect the efficiency relationship being investigated rather than assuming that a particular variable must always be classified in the same way. For example, Serrano-Cinca et al. (2005) treated unique visitors as an output when evaluating internet companies whose objective included generating web impact. In contrast, Arsu (2021) treated the number of social media followers and average viewers as inputs when examining how organisations transformed their existing audience and market resources into sporting and financial outcomes. The latter provides a relevant precedent

for conceptualising audience size as an existing resource base rather than necessarily as an outcome of the production process.

Accordingly, the present study treats the number of users as a scale-related audience input. The variable represents the existing audience base available to each platform for generating advertising reach and revenue. Together with employees and expenses, it forms the resource configuration against which output generation is assessed. This classification does not imply that having fewer users is inherently preferable. Rather, the study examines how effectively platforms utilise their existing audience scale and operational resources to generate the specified outputs. This interpretation is also compatible with the resource-mobilisation perspective in social commerce, in which customer engagement and related digital resources are examined in relation to operational efficiency (Liu et al., 2022).

The objective of this study is therefore to evaluate the relative performance efficiency of eleven prominent social media digital marketing platforms operating in Malaysia. A three-stage analytical approach is adopted. First, the CCR input-oriented DEA model is employed to identify relatively efficient and inefficient platforms. Second, Cross Efficiency is applied to provide greater discrimination among platforms obtaining the maximum CCR efficiency score. Finally, the SBM model is used to further examine the inefficient platforms by explicitly considering input excesses and output shortfalls. Through these complementary DEA approaches, the study provides a multidimensional benchmarking perspective of digital marketing platform efficiency.

## Methodology

The study evaluates eleven social media digital marketing platforms: WhatsApp, Facebook, Instagram, Telegram, TikTok, Facebook Messenger, Twitter, WeChat, LinkedIn, Snapchat, and YouTube. Each platform is treated as a DMU, beginning with WhatsApp as DMU1 and ending with YouTube as DMU11. The analysis uses the 2022 dataset presented in Table 1, with the Malaysian digital-platform information primarily referenced to Kemp (2022).

Three input variables and two output variables were employed. The inputs were number of users, number of employees, and total expenses, while the outputs were potential advertising reach and total annual revenue.

**Table 1: Digital Marketing Platform Data in 2022**

| DMU | Digital Marketing Platform | Inputs          |           |                    | Output                       |                          |
|-----|----------------------------|-----------------|-----------|--------------------|------------------------------|--------------------------|
|     |                            | Users (Million) | Employees | Expenses (Billion) | Potential Ad Reach (Million) | Annual Revenue (Billion) |
| 1   | WhatsApp                   | 24.34           | 3,042     | 0.50               | 20.40                        | 0.906                    |
| 2   | Facebook                   | 23.17           | 75,964    | 4.20               | 21.70                        | 120.18                   |
| 3   | Instagram                  | 20.71           | 18,967    | 3.89               | 15.55                        | 51.40                    |
| 4   | Telegram                   | 17.32           | 281       | 1.08               | 1.60                         | 1.50                     |
| 5   | TikTok                     | 14.59           | 8,424     | 19.20              | 14.59                        | 9.40                     |
| 6   | Facebook Messenger         | 16.09           | 75,964    | 3.20               | 14.59                        | 9.40                     |
| 7   | Twitter                    | 13.00           | 1,300     | 1.52               | 4.40                         | 5.22                     |
| 8   | WeChat                     | 9.85            | 1,375     | 1.30               | 0.10                         | 17.49                    |
| 9   | LinkedIn                   | 7.08            | 19,000    | 9.79               | 6.30                         | 14.50                    |

|    |          |       |       |       |       |       |
|----|----------|-------|-------|-------|-------|-------|
| 10 | Snapchat | 5.17  | 5,288 | 5.997 | 1.35  | 4.52  |
| 11 | YouTube  | 23.60 | 2,800 | 19.00 | 23.60 | 29.20 |

The selection of input and output variables was informed by previous studies that applied DEA to internet companies, online networks, social media, and digital marketing environments (Serrano-Cinca et al., 2005; Martínez-Núñez & Pérez-Aguilar, 2014; Moravcikova & Krizanova, 2019; Bal & Deniz, 2020; Kongar & Adebayo, 2021). The classification of the variables reflects the specific resource-conversion process examined in this study.

In particular, number of users is treated as an existing audience-base input rather than as an outcome to be maximised. In platform-based business environments, a large user community represents an existing scale from which advertising exposure and revenue can be generated. Arsu (2021), for example, incorporated the number of social media followers and average number of viewers as inputs when evaluating organisational efficiency. Thus, the present study evaluates the extent to which a given audience base, together with employees and expenditure, is transformed into potential advertising reach and revenue.

The CCR input-oriented specification was selected because the analytical focus concerns the efficiency with which platforms utilise their existing resource configuration while maintaining observed output levels. Input-oriented DEA has also been used in comparable digital and service environments. Kotnisa and Guzowska (2021) applied an input-oriented CCR model in evaluating social-network activities, while Ishaq and Ajibesin (2022) employed an input-oriented constant-returns-to-scale DEA model to evaluate mobile network operators.

An output-oriented model was not adopted because the principal research question in this study does not concern the maximum proportional expansion of advertising reach and revenue from a fixed input bundle. Instead, the study focuses on resource-utilisation efficiency—that is, how efficiently each platform's existing scale and operational resources support its observed marketing and financial outcomes.

Importantly, the input-oriented specification should not be interpreted as a recommendation that platforms deliberately reduce their user communities. The number of users functions as a scale-related benchmarking input reflecting the audience base available for monetisation. Managerial interpretation of potential resource adjustment is therefore more directly relevant to controllable operational resources, particularly employees and expenditure.

The adequacy of the number of DMUs relative to the number of input and output variables was also considered. A commonly applied DEA rule of thumb is:

$$N \geq 2(m+s)$$

where  $N$  denotes the number of DMUs,  $m$  is the number of inputs, and  $s$  is the number of outputs (Golany & Roll, 1989). With three inputs and two outputs, the minimum number required under this rule is:

$$2(3+2)=10.$$

The present study contains eleven DMUs and therefore satisfies this dimensionality rule. Meeting the rule supports an appropriate relationship between the number of variables and the number of observations; however, it should not be interpreted as guaranteeing the accuracy of

the results by itself. LINGO 19.0 and Microsoft Excel were utilised to perform the DEA calculations and organise the resulting efficiency scores.

### CCR Input-Oriented Model

The CCR model was introduced by Charnes, Cooper, and Rhodes (1978) to evaluate the relative efficiency of comparable DMUs under the assumption of constant returns to scale. In an input-oriented model, efficiency is assessed according to the extent to which the input bundle can be proportionally contracted while maintaining the observed output levels.

For DMU  $o$ , the input-oriented CCR envelopment model is expressed as:

$$\min \theta_o \quad (1)$$

subject to:

$$\sum_{j=1}^N \lambda_j x_{ij} \leq \theta_o x_{io}, \quad i = 1, \dots, m \quad (2)$$

$$\sum_{j=1}^N \lambda_j y_{rj} \geq y_{ro}, \quad r = 1, \dots, s \quad (3)$$

$$\lambda_j \geq 0, \quad j = 1, \dots, N \quad (4)$$

where  $x_{ij}$  represents input  $i$  for DMU  $j$ ,  $y_{rj}$  represents output  $r$  for DMU  $j$ ,  $\lambda_j$  represents the intensity variable, and  $\theta_o$  represents the efficiency score of the DMU under evaluation.

A DMU with  $\theta_o=1$  is located on the CCR efficient frontier, whereas  $\theta_o < 1$  indicates relative inefficiency. The CCR model provides the initial efficiency classification for the eleven platforms. Because several DMUs may receive an efficiency score of 1.00, an additional procedure is required to discriminate among the CCR-efficient units.

### Cross Efficiency Model

Cross Efficiency extends conventional DEA by combining self-evaluation with peer evaluation. While conventional CCR DEA allows each DMU to choose the most favourable weights for its own evaluation, this flexibility can result in several DMUs simultaneously achieving an efficiency score of 1.00. Consequently, conventional CCR scores may not provide sufficient discrimination for ranking the efficient units.

Cross Efficiency addresses this limitation by applying the optimal weights derived from one DMU to the remaining DMUs (Liu et al., 2019). The cross-efficiency score assigned to DMU  $k$  using the optimal weights of DMU  $o$  is:

$$E_{ok} = \frac{\sum_{r=1}^s u_{ro}^* y_{rk}}{\sum_{i=1}^m v_{io}^* x_{ik}} \quad (5)$$

where  $u_{ro}^*$  and  $v_{io}^*$  represent the optimal output and input weights obtained from the DEA evaluation of DMU o. The resulting cross-efficiency matrix is illustrated in Table 2.

**Table 2: Cross-Efficiency Matrix**

| Evaluating DMU | DMU1     | DMU2     | DMU3     | ... | DMUN     |
|----------------|----------|----------|----------|-----|----------|
| DMU1           | $E_{11}$ | $E_{12}$ | $E_{13}$ | ... | $E_{1N}$ |
| DMU2           | $E_{21}$ | $E_{22}$ | $E_{23}$ | ... | $E_{2N}$ |
| DMU3           | $E_{31}$ | $E_{32}$ | $E_{33}$ | ... | $E_{3N}$ |
| ...            | ...      | ...      | ...      | ... | ...      |
| DMUN           | $E_{N1}$ | $E_{N2}$ | $E_{N3}$ | ... | $E_{NN}$ |

The average Cross Efficiency for DMU kk is calculated as:

$$\bar{E}_k = \frac{1}{N} \sum_{o=1}^N E_{ok} \quad (6)$$

A higher mean Cross Efficiency indicates stronger performance under peer evaluation. In this study, Cross Efficiency is particularly important because several platforms achieve a CCR score of 1.00. The approach therefore provides additional discrimination among these efficient platforms instead of treating them as equally ranked.

### Slack-Based Measure Model

The Slack-Based Measure (SBM) developed by Tone (2001) provides a non-radial efficiency measure that explicitly incorporates input excesses and output shortfalls. Unlike a purely radial measure, SBM can identify inefficiency associated with individual inputs and outputs.

For DMU oo, the SBM efficiency measure is expressed as:

$$\rho_o = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s} \sum_{r=1}^s \frac{s_r^+}{y_{ro}}} \quad (7)$$

subject to:

$$x_o = X\lambda + s^-$$

$$y_o = Y\lambda - s^+$$

$$\lambda \geq 0, \quad s^- \geq 0, \quad s^+ \geq 0 \quad (8)$$

where  $s_i^-$  represents input excess,  $s_r^+$  represents output shortfall, and  $\lambda$  represents the intensity variables used to construct the reference benchmark.

The SBM score ranges from zero to one, with a value of one indicating efficiency. The model therefore complements the CCR analysis by considering slack-related inefficiencies that may not be completely captured by proportional input contraction. In this study, the SBM model was applied to the platforms identified as inefficient under the initial CCR analysis.

## Results and Discussion

The efficiency results obtained from the CCR input-oriented, Cross Efficiency, and SBM models are presented in Table 3.

**Table 3: Efficiency Scores of the Social Media Digital Marketing Platforms**

| DMU | Social Media Platform | CCR Score | Cross-Efficiency Score | CE Rank | SBM Score |
|-----|-----------------------|-----------|------------------------|---------|-----------|
| 1   | WhatsApp              | 1.0000    | 0.727                  | 3       | —         |
| 2   | Facebook              | 1.0000    | 0.618                  | 4       | —         |
| 3   | Instagram             | 1.0000    | 0.590                  | 5       | —         |
| 4   | Telegram              | 0.7900    | —                      | —       | 0.5226887 |
| 5   | TikTok                | 1.0000    | 0.816                  | 2       | —         |
| 6   | Facebook Messenger    | 1.0000    | 0.560                  | 6       | —         |
| 7   | Twitter               | 0.7200    | —                      | —       | 0.5801725 |
| 8   | WeChat                | 1.0000    | 0.00879                | 7       | —         |
| 9   | LinkedIn              | 0.9000    | —                      | —       | 0.5302961 |
| 10  | Snapchat              | 0.3376    | —                      | —       | 0.2300745 |
| 11  | YouTube               | 1.0000    | 0.869                  | 1       | —         |

### CCR Efficiency

The CCR input-oriented analysis identified seven platforms as relatively efficient: WhatsApp, Facebook, Instagram, TikTok, Facebook Messenger, WeChat, and YouTube. Each platform obtained a CCR efficiency score of 1.00 and therefore lies on the estimated CCR efficient frontier.

Four platforms were identified as relatively inefficient: Telegram, Twitter, LinkedIn, and Snapchat. LinkedIn achieved a CCR efficiency score of 0.90, followed by Telegram at 0.79 and Twitter at 0.72. Snapchat recorded the lowest CCR score of 0.3376, indicating the largest relative efficiency gap among the eleven platforms.

These results should be interpreted within the particular input-output specification adopted in the study. A platform classified as efficient is not necessarily the universally “best” social media platform. Rather, it is relatively efficient in transforming the specified combination of audience scale, employees, and expenses into potential advertising reach and annual revenue when compared with the other DMUs in the sample.

### Cross-Efficiency Results

Because seven platforms obtained the maximum CCR score of 1.00, the conventional CCR results alone could not differentiate their relative standing. Cross Efficiency was therefore applied to provide additional discrimination based on peer evaluation.

YouTube recorded the highest Cross Efficiency score of 0.869 and ranked first, followed by TikTok with a score of 0.816. WhatsApp ranked third with 0.727, followed by Facebook with 0.618, Instagram with 0.590, and Facebook Messenger with 0.560.

Although WeChat achieved a CCR efficiency score of 1.00, its Cross-Efficiency score was considerably lower at 0.00879, placing it seventh among the CCR-efficient platforms. This result illustrates an important distinction between conventional DEA self-evaluation and Cross Efficiency peer evaluation. A DMU may achieve frontier status using its own favourable weight

structure while receiving substantially lower evaluations when assessed using the weight structures of other DMUs.

Thus, Cross Efficiency provides useful discriminatory information beyond the initial CCR classification. Within the present dataset, YouTube and TikTok demonstrated the strongest peer-evaluated efficiency among the seven CCR-efficient platforms.

### SBM Results

The SBM model was used to further assess the four platforms that were inefficient under the CCR model. Telegram obtained an SBM score of 0.5226887, Twitter 0.5801725, LinkedIn 0.5302961, and Snapchat 0.2300745.

The SBM findings reinforce the CCR results by showing that the same four platforms remain inefficient when input excesses and output shortfalls are explicitly incorporated into the assessment. Among these platforms, Twitter obtained the highest SBM efficiency score, while Snapchat again recorded the lowest value.

Snapchat's relatively low SBM score indicates that its efficiency gap is not represented solely by proportional input contraction; slack-related inefficiency also contributes to its position relative to the efficient frontier.

However, the SBM scores reported in this study should not by themselves be interpreted as exact managerial adjustment targets. Precise recommendations concerning the amount by which individual inputs should be reduced or outputs increased would require the corresponding slack and projection values. Accordingly, the present SBM analysis is interpreted as an additional measure of the relative extent of inefficiency rather than as a set of exact numerical improvement targets.

### Overall Discussion and Managerial Implications

The three DEA approaches provides complementary information. The CCR model identifies which platforms form the relative efficient frontier, Cross Efficiency provides greater discrimination among the CCR-efficient platforms, and the SBM model incorporates input and output slacks when assessing the inefficient platforms.

The results also demonstrate why platform performance should not be judged solely by the size of its user community. A large audience base does not automatically imply high efficiency if that audience, together with other operational resources, does not translate effectively into advertising reach and financial outcomes. The relevant question in this study is therefore not simply how many users a platform possesses, but how effectively its existing audience scale and operational resources are converted into the selected outputs.

This interpretation is important in relation to the treatment of number of users as an input. The model does not imply that reducing the user community is a desirable marketing strategy. Rather, the user variable establishes the scale of the audience resource available to the platform. In practical terms, managerial attention should be directed more strongly towards the utilisation of controllable operational resources such as expenditure and human resources and towards improving the ability to generate advertising reach and revenue from the platform's existing audience base.

This interpretation is consistent with the broader use of audience and engagement resources in efficiency analysis. Arsu (2021) demonstrated that audience-related variables such as social media followers and average viewers can be incorporated as DEA inputs when the analytical objective concerns the efficiency with which an existing audience base contributes to subsequent outcomes. Similarly, Liu et al. (2022) demonstrated the relevance of customer engagement and resource mobilisation in explaining operational efficiency in social-commerce environments.

### Conclusion

This study evaluated the relative performance efficiency of eleven prominent social media digital marketing platforms in Malaysia using CCR input-oriented DEA, Cross Efficiency, and the Slack-Based Measure model. Three inputs which are number of users, number of employees, and total expenses and two outputs which are potential advertising reach and total annual revenue were considered.

The CCR analysis classified seven platforms as relatively efficient and identified Telegram, Twitter, LinkedIn, and Snapchat as inefficient. Since the seven efficient platforms each obtained a CCR score of 1.00, Cross Efficiency was applied to improve discrimination among them. YouTube obtained the highest Cross Efficiency score, followed by TikTok and WhatsApp. The SBM analysis subsequently confirmed the relative inefficiency of Telegram, Twitter, LinkedIn, and Snapchat when input excesses and output shortfalls were explicitly considered.

The combination of the three DEA approaches provides complementary perspectives on platform performance. CCR provides an initial frontier-based efficiency classification, Cross Efficiency facilitates peer-based discrimination among efficient units, and SBM provides additional information on slack-related inefficiency. The combined framework therefore provides a more informative efficiency assessment than reliance on a single DEA score.

The findings also have practical implications for digital marketing decision-making. Platform popularity or audience size alone should not be interpreted as evidence of efficient performance. Decision-makers should consider how effectively the resources and audience scale associated with a platform are converted into advertising and financial outcomes. In the present model, the number of users represents an existing audience-base resource for benchmarking rather than a managerial target that should simply be minimised.

Several limitations should be recognised. First, the results measure relative efficiency among the eleven selected platforms and therefore should not be interpreted as absolute measures of platform quality. Second, DEA results depend on the selected input and output variables. Third, the classification of audience size as an input reflects the particular production process and research objective adopted in this study; alternative research objectives may reasonably conceptualise audience-related variables differently. Finally, the analysis is based on a single-period dataset.

Future studies may extend the analysis using longitudinal data, additional performance indicators, alternative DEA specifications, and sensitivity analysis. Future research may also investigate whether efficiency classifications remain stable when alternative treatments of audience-related variables are considered.

Overall, the study demonstrates that DEA provides a useful decision-support and benchmarking framework for assessing social media digital marketing platforms where performance involves multiple resource and outcome dimensions.

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