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ORIGINAL RESEARCH

An integrated multiple objective decision making approach for exploring the competitiveness of pharmaceutical multinational enterprises

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Abstract
This study integrated multiple objective decision-making approaches including data envelopment analysis (DEA), rough set theory and TOPSIS method for exploring the competitiveness of pharmaceutical multinational enterprises. Firstly, this study applied an advanced two-stage network DEA to measure the R&D efficiency and business performance of pharmaceutical multinational enterprises (PMNEs) listed in the Forbes Global 2000 and ranked these PMNEs by using rough set theory, DEA and TOPSIS method. In addition, differences in environmental, social, and governance (ESG) performance across three continents were investigated. Findings show that North America is significantly the best (worst) region in terms of business performance (R&D efficiency) while Europe is significantly the best (worst) region in terms of R&D efficiency (business performance). Alfresa Holdings Corporation, a PMNE from Japan, is the only PMNE that is efficient from both an R&D and business performance perspective. European PMNEs have significantly better environmental and social performance than other regions, however, they have the worst governance performance. Overall, this study provides insights to managers and investors into the application of various methods for accurately measuring performance and ranking multinational enterprises.

Keywords Rough set theory · TOPSIS · Data envelopment analysis (DEA) · ESG performance · Pharmaceutical industry

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1 Introduction

The pharmaceutical industry is one of the most important and competitive industries in the world, it not only has a critical role in the health maintenance of individuals but also in economic growth (Sharma & Modgil, 2019). Pharmaceutical firms have spent a substantial proportion of their time and investment in research and development (R&D) (Rao, 2020). In 2018, R&D expenditure in the pharmaceutical industry was 179 billion U.S. dollars globally (Mikulic, 2020). A correct grasp of the R&D efficiency of the industry is required to improve resource allocation and thereby prevent either excess or shortage of resource inputs (Liu & Lyu, 2020). According to Lu et al. (2019), evaluating multiple indicators simultaneously is useful for appropriate decision-making. An overall efficiency can be decomposed into two stages of efficiencies (Kao & Hwang, 2008), suggesting that we should also evaluate the sub-processes of a firm (Kao & Hwang, 2011). That is, managers should evaluate their firm performance not only from a multidimensional perspective but also from those of its internal processes. As mentioned in the research of Sharma and Modgil (2019), business performance additionally depends on cost reduction of manufacturing operations and improving the firm's innovative ability. Recently, Hsieh et al. (2020) have applied two-stage data envelopment analysis (DEA) to investigate organizations' innovation and business performance by investigating the network structures of decision-making units (DMUs).

In the present study, we propose a two-stage DEA structure to measure the performance of pharmaceutical multinational enterprises (PMNEs). According to Cook and Zhu (2014), researchers can utilize two-stage network DEA models such as additive efficiency decomposition (AED), multiplicative efficiency decomposition (MED), or multiplicative efficiency aggregation (MEA). However, in AED one is required to predetermine the weights of the two stages of efficiency (Guo et al., 2017). Although predetermining weights are not demanded in a MED model, MED cannot be applied when outputs from the first stage are not the inputs of the second stage and in cases of variable returns to scale (VRS) (Chen & Zhu, 2017, 2019). To overcome the previous limitations, MEA is suitable for a generalized two-stage network DEA model but this model is restricted by nonlinearity. Similarly, to the approach employed by Chen and Zhu (2017, 2019), this study integrates MEA in a two-stage network DEA model with the second-order cone programming (SOCP) technique. The integration helps us solve the nonlinearity matter and deals with the problem of outputs from the first stage are not inputs in the second stage, as well as that of VRS. Additionally, we can only rank the PMNEs by using the obtained DEA scores without consideration of the impacts of different combinations of inputs, intermediates, and outputs. To overcome this shortcoming, rough set theory is further applied to rank the PMNEs for eliminating biased rankings (Lu et al., 2019).

Generally, this study consists of the following objectives. Firstly, we propose a general two-stage network structure, which can simultaneously measure the internal R&D efficiency and business performance of the 41 PMNEs. Secondly, based on 41 PMNEs belonging to different continents, the average environmental, social, and governance (ESG) scores of each continent in the period 2014–2018 are calculated to investigate differences of ESG performance across three continents in our research. Thirdly, we combine rough set theory and DEA for ranking the PMNEs in terms of their R&D efficiency and business performance. Then, a comparison among three ranking approaches is performed to see correlations of the ranking methods.

This study makes at least three contributions. First, the study proposes an integrated multiple objective decision-making approach for evaluating the efficiencies of pharmaceutical

multinational firms. Specifically, the integration of rough set theory and an advanced DEA model provides rankings that are accurate. Second, the proposed performance evaluation approach can serve as a reference for managers at PMNEs in their decision-making process. For example, rough set theory classifies the PMNEs' performance after examining the impacts of the condition attribute on sensitivity of inclusion/exclusion of inputs, intermediates, and outputs. In other words, managers can know the importance of each performance indicator. Third, we examine differences in the ESG scores of the PMNEs among different geographic regions (America, Asia, and Europe). This acts as a guide for investors, managers, and other stakeholders when attempting to move their ESG initiatives further.

2 Literature review

2.1 DEA and TOPSIS methods

DEA is a non-parametric mathematical method to measure the performance of a group of equivalent DMUs by using multiple inputs and multiple outputs (Charnes et al., 1978). It is noteworthy to mention that since DEA does not consider noise, all deviations from the efficient frontier are measured as technical inefficiency (Robaina-Alves et al., 2015). Charnes et al. (1978) initiated the basic DEA model (the CCR model) to evaluate the efficiency of DMUs. Subsequently, other DEA versions have been advanced to improve the accuracy of the efficiency score. For example, Banker et al. (1984) introduced the modified DEA model (BCC model) which slightly reformed the CCR model based on the assumption of a variable return to scale. There is a sizeable literature on DEA, many studies have applied different DEA models to measure the performance of manufacturing and service operations in diverse areas (Lim et al., 2011). Particularly, DEA applications have been mostly applied in health care (Kohl et al., 2019; Lindlbauer et al., 2016; Misiunas et al., 2016), banking (Avkiran, 2015; Wang et al., 2014; Zhou et al., 2019), transportation (Chao et al., 2018; Gutiérrez et al., 2014; Kuo et al., 2020), agriculture (Atici & Podinovski, 2015; Cherchye & Van Puyenbroeck, 2007), education (Lee & Worthington, 2016; Wolszczak-Derlacz, 2017) and the environmental, energy issues that apply the two-step contextual analysis and network DEA have the most rapid growth recently (Liu et al., 2013).

Chen and Hwang (1992) introduced the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) technique that identifies a solution with the shortest distance to the ideal solution and the greatest distance from the negative ideal solution. Rakhshan (2017) proposed a combined method named TOPSIS-DEA for ranking efficient units which includes the benefits of both DEA and multiple criteria decision-making methods. Namazi and Mohammadi (2018) explored innovation efficiency issues as a novel perspective to the resource curse literature using the TOPSIS-DEA method. The authors (Namazi & Mohammadi, 2018) indicate that nations with low innovation performance have little chance of enhancing their innovation efficiency and growth. Recently, Wang et al. (2019) adopted the DEA-TOPSIS method for multi-attribute decision-making to improve industry efficiency. In the study (Wang et al., 2019), DEA is used to measure the efficiency scores while the TOPSIS is applied to rank substitute decision-making schemes.

2.2 Evaluating the performance of the pharmaceutical industry

This study measures the performance of PMNEs by the adoption of the DEA approach. Although there are other methods used to measure the performance of firms, DEA is considered as a suitable method because DEA can explore firms' multiple input–output data by comparison and this method does not demand any normality assumptions. Previous researchers have applied DEA to investigate the performance of firms in the pharmaceutical industry (Al-Refaie et al., 2019; Banerjee, 2019; Gascón et al., 2017; Liu & Lyu, 2020).

Gascón et al. (2017) measured the performance of large pharmaceutical firms by applying the DEA approach. The authors used a sample of 37 large pharmaceutical laboratories within the 2008–2013 time period. Gascón et al. (2017) stated that the pharmaceutical industry is extremely competitive since there are many firms at the efficient frontier and many other firms close to this border. Al-Refaie et al. (2019) applied DEA window analysis for measuring the efficiency of the blistering process in the pharmaceutical industry. From the results, the author presented valuable feedback on how to enhance efficiency, resource utilization, and successfully handle production lines. An overall efficiency can be decomposed into two stages of efficiencies (Kao & Hwang, 2008), suggesting that we should also evaluate the sub-processes of a firm (Kao & Hwang, 2011). That is, managers should evaluate their firm performance not only from a multidimensional perspective but also from those of its internal processes. Recently, Liu and Lyu (2020) investigated the innovative efficiency of the pharmaceutical industry in China based on a two-stage dynamic network DEA model.

However, one of the most popular topics in organizational studies is firm performance measurement (Miller et al., 2012). Various firms may highlight different performance evaluations (Tsai et al., 2020). Previous studies considered different types of performance (Bacinello et al., 2019; Huang & Li, 2017; Prajogo, 2016; Tsai et al., 2020). The operational performance depends on decreasing the cost of manufacturing operations and improving the firm's R&D efficiency (Sharma & Modgil, 2019). The pharmaceutical industry is an innovation-intensive industry with high R&D spending (Mazzucato & Parris, 2015). In 2018, R&D expenditure in the pharmaceutical industry is 179 billion U.S. dollars globally (Mikulic, 2020). Although the R&D investment of the pharmaceutical industry has increasingly expanded every year, the overall effect is unobvious (Liu & Lyu, 2020). According to the previous authors (Chen et al.2014; Nemlioglu & Mallick, 2017; Yang & Okada, 2019; Yu & Hong, 2016), a high R&D investment can convert innovative performance into tangible assets through patents to gain firm performance. Companies normally gain knowledge and convert it into technologies and products, then utilize their innovative ability to produce revenue (Chen et al., 2018) and market value (Wang et al., 2013).

2.3 Environmental, social and governance (ESG) performances of the pharmaceutical industry

In recent years, firms have increasingly faced pressure from society to present information on their ESG performances (Liagkouras et al., 2020), which are the basic modern dimensions of corporate social responsibility(CSR) (Miralles-Quirós et al., 2018). The ESG performance of firms has increased in importance for policymakers and investors (Nekhili et al., 2019). Currently, an increasing number of firms have understood that ESG is the main driving force for reputation creation (Aouadi & Marsat, 2018). Stakeholders can judge firm performance basing on ESG reports and ratings (Auer & Schuhmacher, 2016; Limkriangkrai et al., 2017). Auer and Schuhmacher (2016) explored the performance of socially responsible investments

in regions (the Asia–Pacific, the United States, and Europe) by applying a variety of portfolio screens. According to Auer and Schuhmacher (2016), investors can pursue an ethical managerial style and still achieve a performance similar to the broad market in the Asia–Pacific region and in the United States. However, investors in Europe tend to pay a premium for socially responsible investment, depending on the industry concentration. Following a previous perspective (Auer & Schuhmacher, 2016), we determine whether differences exist in different locations (America, Asia, and Europe region) for ESG scores.

3 Research design

3.1 Two-stage production process of pharmaceutical multinational enterprises

In this study, we measure firm performance from a two-stage perspective (Kao & Hwang, 2011) namely R&D efficiency and business performance, by integrating a two-stage network DEA and SOCP technique (Chen & Zhu, 2017). As can be seen from Fig. 1, the former stage measures R&D efficiency of PMNEs while the later stage focuses on the business performance of the PMNEs. In the first stage, R&D expenditure is utilized to produce three intermediate outputs: patent citation, patent application and granted patent. In the second stage, these three intermediate outputs are utilized as inputs together with three additional elements (operating expenses, property, plant & equipment and employee) to produce two final outputs comprising revenue and market value. Sources for indicators used to measure R&D efficiency and business performance are summarized in Table 1. These indicators have been selected to ensure consistency in measuring performance in the two stages, with definitions for each indicator provided in Table 2.

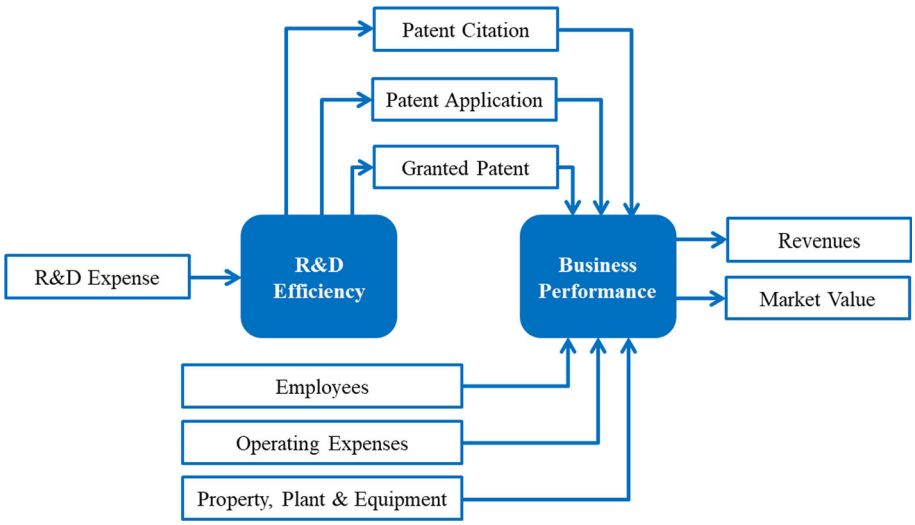

Fig. 1 The two-stage network production process structure of PMNEs

Table 1 Input/output indicators and referenced sources

Indicator	Unit	The studies that include the indicator
R&D expense	US dollar thousand	Chen et al. (2018), Karadayi and Ekinci (2019) and Wang et al. (2013)
Patent citation	Item	Huang et al. (2018) and De Carolis (2003)
Patent application	Item	Chen et al. (2018), Wang et al. (2016) and Yang and Okada (2019)
Granted patent	Item	Carrillo (2019), Karadayi and Ekinci (2019) and Qin et al. (2019)
Employees	Person	Chen et al. (2018), Guan and Chen (2010), Karadayi and Ekinci (2019) and Wang et al. (2013)
Operating expenses	US dollar thousand	Liu et al. (2017) and Wang et al. (2017)
Property, plant & equipment	US dollar thousand	Chen et al. (2018) and Wang et al. (2013)
Revenues	US dollar thousand	Li et al. (2019), Liu et al. (2017), Wang et al. (2013) and Wang et al. (2017)
Market value	US dollar thousand	Wang et al. (2013), Wang et al. (2017) and Yang and Okada (2019)

Table 2 Definitions of indicators

The process	Indicators	Definitions
Input to IP	R&D expense	Represents all direct and indirect costs related to the creation and development of new processes, techniques, applications, and products with commercial possibilities
Output from IP/input to BP	Patent citation	Reflects the citation times of a specific patent by other companies
Output from IP/input to BP	Patent application	Reflects the number of requests pending at a patent office for the grant
Output from IP/input to BP	Granted Patent	Reflects the number of patents granted
Input to BP	Employees	The number of both full and part-time employees of the company
Input to BP	Operating expenses	The sum of all expenses related to operations
Input to BP	Property, plant & equipment	Represents gross property, plant, and equipment less accumulated reserves for depreciation, depletion, and amortization
Output from BP	Revenues	Gross sales and other operating revenue less discounts, returns and allowances
Output from BP	Market value	The current total market value of a company based on the current price and current shares outstanding

Table 3 Descriptive statistics of I/M/O factors for DEA analysis

Input/output factors	Mean	Percentile 25	Percentile 75	Std dev	K-S test[a]
R&D expense	2,618,660	485,686	3,901,200	2,845,218	$p < .01$
Patent citation	749	246	913	901	$p < .10$
Patent application	487	86	538	708	$p < .05$
Granted patent	281	52	300	407	$p < .01$
Employees	36,712	7802	48,852	37,777	$p < .05$
Operating expenses	18,242,040	3,583,825	20,155,312	29,218,196	$p < .01$
Property, plant & equipment	4,775,338	1,031,429	6,508,000	5,204,669	$p < .05$
Revenues	22,082,156	4,791,051	23,894,600	31,285,184	$p < .01$
Market value	67,258,605	16,210,158	96,995,713	71,946,639	$p < .05$

[a]Kolmogorov–Smirnov test

3.2 Data collection and description

We explore the performance of multinational enterprises from the list of largest public enterprises in the pharmaceutical industry (Forbes, 2019). During the sample period, there are 63 PMNEs on the list. Data on financial indicators used to measure firm performance and ESG scores are extracted from the Thomson Reuters database. The numbers of patent citations, patent applications and granted patents are collected from The Lens database. Due to the unavailability of data on R&D expenses, ESG scores, and patents, 22 PMNEs are excluded from the analysis and the final sample comprises 41 PMNEs. Table 3 shows the descriptive statistics for indicators of 41 PMNEs. Table 4 shows that the indicators have a positive correlation following the isotonic condition used to evaluate the efficient level. Most of the indicators have a non-normal distribution (Kolmogorov–Smirnov test significant), indicating that the DEA method is a powerful research technique because the assumption of normality for data is not required (Lin et al., 2019).

3.3 Multiplicative efficiency aggregation in SOCP

In this research, we investigate the two-stage structure of PMNEs by using cross-sectional data. To examine the impacts of variations between input items and output indicators in terms of efficiency, this research integrates a two-stage network DEA and SOCP technique to measure the R&D efficiency and business performance. Related procedures are described below:

The two-stage network structure (Fig. 1) considers n PMNEs. We assume that each of the n PMNEs consumes a inputs $x_{ij}(i = 1, \ldots, a;\ j = 1, \ldots, n)$ to produce b outputs $m_{qj}(q = 1, \ldots, b;\ j = 1, \ldots, n)$ in the first stage. These b outputs, which are termed intermediate links, integrate with c additional inputs $ex_{kj}(k = 1, \ldots, c;\ j = 1, \ldots, n)$ that next enter the second stage to generate d final outputs $y_{lj}(l = 1, \ldots, d;\ j = 1, \ldots, n)$.

Following the VRS assumption, this research employs MEA to calculate overall technical efficiency in the two-stage production process. The overall efficiency of selected PMNEs

Table 4 Correlation coefficient among all input and output factors

	1	2	3	4	5	6	7	8	9
1.R&D expense	1								
2.Patent citation	0.679***	1							
3.Patent application	0.668***	0.876***	1						
4.Granted patent	0.676***	0.837***	0.991***	1					
5.Employees	0.766***	0.585***	0.713***	0.736***	1				
6.Operating expenses	0.297*	0.163	0.241	0.253	0.543***	1			
7.Property, plant & equipment	0.936***	0.693***	0.748***	0.754***	0.875***	0.359**	1		
8.Revenues	0.412***	0.244	0.318**	0.332**	0.624***	0.990***	0.466***	1	
9.Market value	0.924***	0.605***	0.600***	0.623***	0.793***	0.342**	0.875***	0.464***	1

***, ** and * denote significance at the 1%, 5% and 10% level, respectively

$MNE_o (o = 1, \ldots, n)$ is measured by the following formula:

$$
\begin{aligned}
&Max \ \frac{\left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right)}{\sum_{i=1}^{a} v_i x_{io}} \cdot \frac{\left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right)}{\left(\sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k e x_{ko}\right)} \\
&S.T. \\
&\left(\sum_{q=1}^{b} w_q m_{qj} + u_1\right) \Big/ \sum_{i=1}^{a} v_i x_{ij} \le 1, \ (j = 1, \ldots, n) \\
&\left(\sum_{l=1}^{d} \mu_l y_{lj} + u_2\right) \Big/ \left(\sum_{q=1}^{b} w_q m_{qj} + \sum_{k=1}^{c} \eta_k e x_{kj}\right) \le 1, \ (j = 1, \ldots, n) \\
&v_i, w_q, \eta_k, \mu_l \ge \varepsilon, \ \forall i, q, k, l, \\
&u_1, u_2 \text{ free in sign,}
\end{aligned} \tag{1}
$$

where v_i, w_q, η_k, μ_l are positive weights, u_1, u_2 are free variables under the VRS assumption, by integrating the small non-Archimedean ε in two-stage network DEA. We assumed the weights w_q on the intermediate measures are equal between the two stages. Measurements of R&D efficiency and business performance for a PMNE can be presented as

$$
\frac{\left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right)}{\sum_{i=1}^{a} v_i x_{io}} \text{ and } \frac{\left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right)}{\left(\sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k e x_{ko}\right)}
$$

We equivalently modified the Eq. (1) to be Eq. (2) as

$$
\begin{aligned}
&Min \ \frac{\sum_{i=1}^{a} v_i x_{io}}{\left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right)} \cdot \frac{\left(\sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k e x_{ko}\right)}{\left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right)} \\
&S.T. \\
&\left(\sum_{q=1}^{b} w_q m_{qj} + u_1\right) \le \sum_{i=1}^{a} v_i x_{ij}, \ (j = 1, \ldots, n) \\
&\left(\sum_{l=1}^{d} \mu_l y_{lj} + u_2\right) \le \left(\sum_{q=1}^{b} w_q m_{qj} + \sum_{k=1}^{c} \eta_k e x_{kj}\right), \ (j = 1, \ldots, n) \\
&v_i, w_q, \eta_k, \mu_l \ge \varepsilon, \ \forall i, q, k, l, \\
&u_1, u_2 \text{ free in sign,}
\end{aligned} \tag{2}
$$

According to the MEA assumption, Eq. (2) is prevented from being a linear programming problem since this objective function is extremely nonlinear. We follow Chen and Zhu (2019) to solve the problem by calculating a sequence of possible problems of SOCP. We apply an epigraphic transformation to solve the nonlinear programming problem as Eq. (3)

$$
\begin{aligned}
&Min\,\theta_o \\
&S.T. \\
&\frac{\sum_{i=1}^{a} v_i x_{io}}{\left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right)} \cdot \frac{\left(\sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k ex_{ko}\right)}{\left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right)} \le \theta_o \\
&\left(\sum_{q=1}^{b} w_q m_{qj} + u_1\right) \le \sum_{i=1}^{a} v_i x_{ij},\ (j = 1, \ldots, n) \\
&\left(\sum_{l=1}^{d} \mu_l y_{lj} + u_2\right) \le \left(\sum_{q=1}^{b} w_q m_{qj} + \sum_{k=1}^{c} \eta_k ex_{kj}\right),\ (j = 1, \ldots, n) \\
&v_i, w_q, \eta_k, \mu_l \ge \varepsilon,\ \forall i, q, k, l, \\
&u_1, u_2 \text{ free in sign,}
\end{aligned}
\tag{3}
$$

The R&D efficiency and business performance range between zero and one. When we consider a reciprocal of the objective function of Eq. (2) to be a nonlinear constraint in Eq. (3), the value of $\theta_o (o = 1, \ldots, n)$ is from 1 to ∞; hence, $\theta_o \ge 1$ in Eq. (3). The constraint $\frac{\sum_{i=1}^{a} v_i x_{io}}{\left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right)} \cdot \frac{\left(\sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k ex_{ko}\right)}{\left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right)} \le \theta_o$ is similar to the following A matrix

$$
A = \begin{bmatrix} \theta \cdot \left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right) & \left(\sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k ex_{ko}\right) \\ \sum_{i=1}^{a} v_i x_{io} & \left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right) \end{bmatrix} \succ= 0 \tag{4}
$$

where '$\succ=$' indicates that all parts in the A matrix are positive. Furthermore, we equivalently identify Eq. (5) for the matrix A as follows:

$$
\begin{bmatrix} \theta \cdot \left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right) & \\ \frac{1}{2}\left(\sum_{i=1}^{a} v_i x_{io} + \sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k ex_{ko}\right) & \\ \frac{1}{2}\left(\sum_{i=1}^{a} v_i x_{io} + \sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k ex_{ko}\right) & \left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right) \end{bmatrix} \succ= 0 \tag{5}
$$

We note that for any square matrix A, $A > 0$ is similar to $(1/2)(A + A^T) \succ 0$. The semi-definiteness of the Eq. (5) indicates

$$
ac - b^2 \ge 0 \tag{6}
$$

where $a = \theta \cdot \left(\sum_{q=1}^{b} w_q m_{qo} + u_1\right)$, $b = \frac{1}{2}\left(\sum_{i=1}^{a} v_i x_{io} + \sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k ex_{ko}\right)$, and $c = \left(\sum_{l=1}^{d} \mu_l y_{lo} + u_2\right)$.

Equation (6) is equivalent to $\sqrt{b^2 + \left[\frac{1}{2}(a - c)\right]} \le \frac{1}{2}(a + c)$. We identify Eq. (7) by the standard definition of ℓ_2 norm as follows:

$$\left\| \begin{pmatrix} \sum_{i=1}^{a} v_i x_{io} + \sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k e x_{ko} \\ \left(\theta \sum_{q=1}^{b} w_q m_{qo} + \theta u_1 - \sum_{l=1}^{d} \mu_l y_{lo} - u_2\right) \end{pmatrix} \right\|_2 \leq \left(\theta \sum_{q=1}^{b} w_q m_{qo} + \theta u_1 + \sum_{l=1}^{d} \mu_l y_{lo} + u_2\right) \tag{7}$$

The objective function of Eq. (3) can be converted into a SOCP problem that θ is provided. θ is restricted above. Therefore, Eq. (3) is identically converted to Eq. (8). The maximum measure of θ, represented as θ^*, can be approximately achieved by noting the domain of θ, with which we figure out Eq. (3). Lastly, following the techniques from the authors (Chen & Zhu, 2017, 2019), we apply the standard definition of ℓ_2 norm and the SOCP technique to get Eq. (8) to solve a general two-stage network DEA.

$$\begin{aligned} &Min\,\theta \\ &S.T. \\ &\left\| \begin{pmatrix} \sum_{i=1}^{a} v_i x_{io} + \sum_{q=1}^{b} w_q m_{qo} + \sum_{k=1}^{c} \eta_k e x_{ko} \\ \left(\theta \sum_{q=1}^{b} w_q m_{qo} + \theta u_1 - \sum_{l=1}^{d} \mu_l y_{lo} - u_2\right) \end{pmatrix} \right\|_2 \\ &\leq \left(\theta \sum_{q=1}^{b} w_q m_{qo} + \theta u_1 + \sum_{l=1}^{d} \mu_l y_{lo} + u_2\right) \\ &\left(\sum_{q=1}^{b} w_q m_{qj} + u_1\right) \leq \sum_{i=1}^{a} v_i x_{ij},\ (j = 1, \ldots, n) \\ &\left(\sum_{l=1}^{d} \mu_l y_{lj} + u_2\right) \leq \left(\sum_{q=1}^{b} w_q m_{qj} + \sum_{k=1}^{c} \eta_k e x_{kj}\right),\ (j = 1, \ldots, n) \\ &v_i, w_q, \eta_k, \mu_l \geq \varepsilon,\ \forall i, q, k, l, \\ &u_1, u_2 \text{ free in sign,} \end{aligned} \tag{8}$$

The overall efficiency (OE), R&D efficiency (RD) and business performance (BP) for an observed PMNE can be calculated as:

$$\begin{aligned} RD &= \left(\sum_{q=1}^{b} w_q^* m_{qo} + u_1^*\right) \Big/ \sum_{i=1}^{a} v_i^* x_{io}, \\ BP &= \left(\sum_{l=1}^{d} \mu_l^* y_{lo} + u_2^*\right) \Big/ \left(\sum_{q=1}^{b} w_q^* m_{qo} + \sum_{k=1}^{c} \eta_k^* e x_{ko}\right), \\ OE &= RD \times BP. \end{aligned} \tag{9}$$

3.4 Rough set-based ranking approach

Rough set theory has been a useful data analysis tool to deal with fuzzy and uncertain information (Pawlak, 1982, 2012). Based on the advantages of this theory, Lu et al. (2019) assessed the efficiencies of investment trusts companies. In this study, the DEA approach is combined with the rough set theory to rank PMNEs. This integration avoids estimation errors as compared to other DEA ranking methods such as TOPSIS DEA, Game cross-efficiency, and super efficiency (Chen et al., 2013; Liang et al., 2008; Lim & Zhu, 2015; Rakhshan, 2017). Therefore, the following nine steps as mentioned in the work of Lu et al. (2019) are applied in this study.

Step 1: We develop a two-stage network production process structure for PMNEs (Fig. 1). As mentioned in the previous section of this study, we integrate two-stage network DEA and SOCP techniques to measure R&D efficiency and business performance. If the overall efficiency score is equal to 1, $OE = 1$, in Eq. (9), the considered PMNE is called the overall efficiency. If the R&D efficiency score is equal to 1 (less than 1), $RD = 1(< 1)$, then the observed PMNE is technically efficient (inefficient) at stage 1.

Step 2: We consider potential combinations of inputs, intermediates, additional inputs and outputs for each PMNE while computing their efficiency. In this study, we use one input, three intermediaries, three additional inputs, and two outputs (see Fig. 1). Therefore, in the case of fixed input, we investigate the individual effect of intermediates, additional inputs, and outputs indicators on the efficiency scores of the PMNEs. Therefore, a total of 8 (3 + 3 + 2) data sets are analyzed. These 8 different combinations of intermediates, additional inputs, and outputs are analyzed and employed to differentiate efficient units (see Appendices A and B for the obtained efficiency values).

Step 3: From the efficiency scores calculated in Step 2, we choose the combinations of performance indicators in the case of fixed inputs, intermediates, additional inputs, and outputs, respectively. Thus, we can examine the impacts of DEA indicators on the sensitivity of inclusion of inputs, intermediates, additional inputs, and outputs or exclusion of these attributes excepting the input. Notably, because we only have one input in the first stage, the exclusion of input is ignored in the present study. From this step, we can identify the strengths and weaknesses of possible combinations of the indicators by the efficiency analysis model.

Step 4: The continuous score is converted into a discrete value. The efficiency scores calculated by the different potential combinations are determined as the discrete numerical ranges and are changed to equivalent values. We divided the efficiency scores into different ranges (a) 1–0.8 is replaced by the value 4, (b) 0.8–0.5 is replaced by the value 3, (c) 0.5–0.3 is replaced by the value 2, (d) 0.3–0 is replaced by the value 1.

Step 5: The overall efficiency of the two-stage network production process structure for PMNEs is considered as the decision attribute of this study. To create a data set using rough set theory, the overall efficiency scores are categorized into four levels (a) 1–0.8 is replaced by the value 4, (b) 0.8–0.5 is replaced by the value 3, (c) 0.5–0.3 is replaced by the value 2, (d) 0.3–0 is replaced by the value 1.

Step 6: The significance of each condition attribute is measured following the decision attribute's level of dependency on the condition attribute.

Definition 1 Information systems.

Information systems are applied to exhibit knowledge in rough set theory. An information system $S = (U, A, V, f)$ includes U a nonempty, finite set called the universe, which is a set of objects U = $\{dm_1, dm_2, \ldots, dm_n\}$;$A$, a nonempty, finite set of attributes,$A = C \cup D$, in which C is the set of condition attributes and D is the set of decision attributes; $V = \bigcup_{a \in A} V_a$, the domain of a; and $f : U \times A \to V$, an information function. For each $a \in A$ and $dm \in U$, an information function $f(dm, a) \in V_a$ is determined; therefore, for each object dm in U, f indicates its attribute value.

Definition 2 Lower and upper approximation.

Let $A = (U, R)$ be an approximation space and let DM be any subset of U. The R-lower approximation of DM, denoted $\underline{R}(DM)$, and R-upper approximation of DM, $\overline{R}(DM)$ are identified by

$$\underline{R}(DM) = \cup\{[dm]_R \in U/R : [dm] \subseteq DM\} \tag{10}$$

and

$$\bar{R}(DM) = \cup\{[dm]_R \in U/R : [dm] \cap DM \neq \emptyset\} \tag{11}$$

Definition 3 Dependability.

Suppose $S = (U, A, V, f)$ is a decision table. The dependability between condition attribute C and decision attribute D is identified as:

$$k = \gamma_C(D) = \frac{card(POS_C(D))}{card(U)} \tag{12}$$

where card (U) means the cardinal number of sets.

Definition 4 Significance of single attribute and attribute sets.

In the above decision table, the significance of condition attribute subset $C'\left(C' \subseteq C\right)$ related to D is determined as:

$$\sigma_{CD}\left(C'\right) = \gamma_C(D) - \gamma_{C-C'}(D). \tag{13}$$

Specifically, $C' = \{a\}$, the significance of a single attribute $a \in C$ related to D is determined as:

$$\sigma_{CD}\left(C'\right) = \gamma_C(D) - \gamma_{C-\{a\}}(D). \tag{14}$$

Step 7: From the Step 6's results, the condition attribute with a score of 0 is removed to lower excessive attributes and simply compute.

Step 8: The significance of the rough set is transformed to a value by the weighted average approach in which the average weight of the combinations is computed.

Step 9: Rank the PMNEs concerning the weight values from largest to smallest to present a reference for perfect PMNE selection.

4 Empirical analysis

4.1 Pharmaceutical multinational enterprises performance analysis

4.1.1 Performance analysis

Table 5 shows the stage-level efficiency scores (i.e., R&D efficiency and business performance) which obtained from the integration of two-stage network DEA and SOCP technique (Chen & Zhu, 2017). Table 5 reveals that four PMNEs are R&D efficient and twelve are business efficient. Particularly, Alfresa Holdings Corporation, a PMNE from Japan, is the only efficient PMNE for both R&D efficiency and business performance. The average R&D efficiency score of 41 PMNEs is 0.336 and the average business efficiency score is 0.925. The low result of the average R&D efficiency score suggests that R&D performances in the operation of the observed PMNEs are not attracting enough attention.

Concerning the three continents (Asia–Pacific, Europe, and North American), we analyze the average scores of R&D efficiency and business performance to explore the efficient status of these regions (Lin et al., 2020). We compute the average R&D efficiency and business performance scores of PMNEs in each region and display the results in Table 5. The

Table 5 Efficiencies for each PMNE

Region	PMNEs	R&D efficiency	Business performance
Asia–Pacific	Alfresa	1.000	1.000
	Astellas	0.088	0.930
	Celltrion	0.100	1.000
	CSL	0.284	0.807
	CSPC	0.246	0.848
	Daiichi Sankyo	0.126	0.745
	Eisai	0.259	0.694
	Otsuka	0.122	0.706
	Piramal	0.818	1.000
	Shionogi	0.251	0.849
	Takeda	0.055	0.767
	Teva	0.031	0.919
	Average	*0.282*	*0.855*
Europe	Allergan	0.190	1.000
	AstraZeneca	0.054	0.958
	Bayer	1.000	0.602
	DSM	1.000	0.562
	Grifols	0.231	0.840
	H Lundbeck	0.272	0.840
	Ipsen	0.358	0.813
	Medtronic	1.000	0.608
	Merck	0.013	0.833
	Mylan	0.074	0.926
	Novartis	0.936	0.599
	Novo Nordisk	0.158	1.000
	Roche	0.802	0.699
	Sanofi	0.352	0.701
	UCB	0.156	0.837
	Average	*0.440*	*0.788*
North America	Abbott	0.257	0.711
	Abbvie	0.713	1.000
	Alexion	0.157	1.000
	Amgen	0.596	1.000
	Biogen	0.630	0.891
	Eli Lilly	0.044	0.845
	Incyte	0.242	1.000
	Johnson & Johnson	0.164	1.000
	Mckesson	0.095	1.000
	Merck & Company	0.014	0.936
	Pfizer	0.206	0.791
	Regeneron	0.176	0.940

Table 5 (continued)

Region	PMNEs	R&D efficiency	Business performance
	Vertex	0.121	1.000
	Zoetis	0.383	0.830
	Average	*0.271*	*0.925*
Overall	Average	0.336	0.854
Number of efficient PMNEs		4	12
K–W test (p-value)[a]		0.457	0.038**

***, ** and * denote significance at the 1%, 5% and 10% level, respectively
[a]Kruskal–Wallis test

results indicate that North America is ranked as the best (worst) region in terms of business performance (R&D efficiency). Conversely, Europe is ranked as the best (worst) region in terms of R&D efficiency (business performance). Asia–Pacific is ranked as the second-best in terms of R&D efficiency and business performance. A Kruskal–Wallis test shows the statistical significance of differences in business performance scores among the regions.

4.1.2 Sensitivity analysis

One of the main shortcomings of the DEA structure is that efficiency scores wholly depend on the framework's input and output indicators. To overcome the limitations, a sensitivity analysis is conducted to examine the effects of input and output elimination on the DEA efficiency scores. The R&D and business efficiency scores for the various scenarios are stated in Appendix A and Appendix B, respectively. In each scenario, one of the input or output variables has been removed. In all modified frameworks at least one input and one output indicator are required. Nevertheless, the R&D expense indicator is not deleted because it is only the input that the first sub-process has.

In the R&D efficiency stage, removing the patent citation output indicator results in the lowest average efficiency (0.208) (see Appendix A) compared with the average R&D efficiency score including all the input and the output indicators (0.336) (see Table 5). Removing the patent application output indicator in the R&D efficiency stage results in the same average efficiency (0.336) (see Appendix A) compared with the average efficiency score of R&D efficiency including all the input and the output indicators (0.336) (see Table 5).

Similarly, removing the market value indicator in the business performance stage results in the lowest average efficiency (0.394) compared with the average efficiency score of business performance including all the input and the output indicators (0.854). Removing the patent application and granted patent input indicators in the business performance stage result in the same average efficiency (0.854) (see Appendix B) compared with the average efficiency score of business performance including all the input and the output indicators (0.854) (see Table 5).

It is worth remarking that the patent citation indicator and market value indicator have the greatest impact on R&D efficiency and business performance, respectively, while indicators related to patent application and granted patent have no effects on business performance and R&D efficiency. Following the sensitivity analysis findings, the benchmarks of R&D efficiency evaluation in all scenarios considered are DSM, Bayer, and Alfresa (see Appendix

Table 6 Average ESG score analysis of 41 PMNEs according to regions

Region	Number of PMNEs	Average scores		
		Environmental score	Social score	Governance score
Asia–Pacific	12	60.59	64.53	60.93
Europe	15	74.56	79.04	59.80
North America	14	66.96	75.58	67.42
Overall	41	67.88	73.61	62.73
K-W test (p-value)[a]		0.0000***	0.0012***	0.0304**

***, ** and * denote significance at the 1%, 5% and 10% level, respectively
[a]Kruskal–Wallis test

A). However, DSM is the worst PMNEs in the second sub-process (business performance assessment) for all scenarios except one with no market value output (see Appendix B). In the business performance measurement, the benchmarks for all scenarios are Incyte, Celltrion, and Alfresa. The benchmark in both R&D efficiency and business performance for all scenarios is Alfresa.

4.2 ESG score analysis in different regions

Following the approach employed by previous researchers (Auer & Schuhmacher, 2016; Lin et al., 2020), we determine whether differences exist in different locations (North America, Asia–Pacific, and Europe) from an ESG performance perspective. Based on 41 PMNEs belonging to different continents, the average ESG scores of each continent in the period 2014–2018 are shown in Table 6. The Kruskal–Wallis test is applied to investigate differences of ESG performance across three continents in our research. The bottom row of Table 6 displays the non-parametric statistical analysis. The average scores of environmental and social pillars of PMNEs in Europe are synchronously higher than those of other regions. This finding reveals that European PMNEs significantly have better environmental and social performance than other regions. These results confirm that European PMNEs are willing to assume the costs for their environmentally and socially responsible investments (Auer & Schuhmacher, 2016). Conversely, PMNEs in Asia are significantly inefficient in terms of environmental and social performance when compared with those in Europe and North America. For governance, PMNEs in North America are significantly the best performers. Although the PMNEs in Europe are ranked as the best in terms of environmental performance, they are the worst with regard to governance performance. This particular result confirms the finding of Halkos et al. (2015) in which suggests that higher governance performance will not always lead to increased environmental performance.

4.3 Ranking multinational enterprises in the pharmaceutical industry

4.3.1 Rough set-based ranking approach

In this study, we first integrate two-stage network DEA and SOCP technique to estimate the R&D efficiency and business performance of 41 PMNEs. Next, we integrate and apply a

rough set and the DEA for ranking the PMNEs. One of the main advantages of the rough set-based ranking method is that it can be combined with a two-stage DEA. That is, this proposed ranking approach considers multiple performance indicators and also the sub-processes of a firm. Moreover, it avoids estimation errors as compared to other DEA ranking methods (Chen et al., 2013; Liang et al., 2008; Lim & Zhu, 2015; Rakhshan, 2017). Tables 7 and 8 show the empirical results of the two stages.

Table 7 illustrates the ranking of the PMNEs in terms of their R&D efficiency score. Three PMNEs (i.e., DSM, Bayer, and Alfresa) are the most efficient from an R&D perspective, while Teva, Merck, and Merck & Company are ranked as the worst-performing PMNEs.

From a business performance perspective, three PMNEs including Incyte, Celltrion, and Alfresa are identified as the most competent. In contrast, Novartis, Bayer, and DSM are ranked as the worst-performing companies (Table 8). From the results shown in Tables 7 and 8, we found that PMNEs that have a high rank in the first stage (R&D) tend to have a low rank in the second stage (business performance). For example, DSM, Bayer, Medtronic, Novartis are ranked in the top five in the first stage but conversely are ranked as the worst performers in the second stage. Hence, managers should consider improving their performance in the inefficient stage. A notable exception is Alfresa which is ranked as one of the top three most

Table 7 Ranking analysis based on Stage 1- R&D efficiency

PMNEs	Weight[a]	Rankings	PMNEs	Weight	Rankings
DSM	1.000	1	Pfizer	0.187	22
Bayer	1.000	2	Allergan	0.183	23
Alfresa	1.000	3	Regeneron	0.160	24
Medtronic	0.916	4	Johnson & Johnson	0.151	25
Novartis	0.878	5	UCB	0.149	26
Piramal	0.774	6	Novo Nordisk	0.149	27
Roche	0.767	7	Alexion	0.143	28
Abbvie	0.645	8	Daiichi Sankyo	0.120	29
Biogen	0.570	9	Otsuka	0.117	30
Amgen	0.540	10	Vertex	0.113	31
Zoetis	0.365	11	Celltrion	0.100	32
Sanofi	0.350	12	Mckesson	0.089	33
Ipsen	0.346	13	Astellas	0.083	34
CSL	0.264	14	Mylan	0.073	35
H Lundbeck	0.262	15	Takeda	0.052	36
Abbott	0.245	16	Astrazeneca	0.051	37
Eisai	0.240	17	Eli Lilly	0.044	38
Shionogi	0.239	18	Teva	0.035	39
CSPC	0.235	19	Merck	0.023	40
Incyte	0.228	20	Merck & Company	0.019	41
Grifols	0.227	21			

[a]The weight is rounded to 3 decimal places, the top three in their rankings based on the original scores which are not equal to 1

Table 8 Ranking analysis based on Stage 2-Business performance

PMNEs	Weight[a]	Rankings	PMNEs	Weight	Rankings
Incyte	1.000	1	Teva	0.767	22
Celltrion	1.000	2	Shionogi	0.767	23
Alfresa	1.000	3	Zoetis	0.759	24
Mckesson	0.998	4	Ipsen	0.754	25
Vertex	0.974	5	Eli Lilly	0.749	26
Alexion	0.966	6	CSL	0.738	27
Piramal	0.964	7	Pfizer	0.736	28
Johnson & Johnson	0.942	8	Grifols	0.731	29
Novo Nordisk	0.937	9	UCB	0.728	30
Amgen	0.912	10	Roche	0.647	31
Abbvie	0.909	11	Takeda	0.645	32
Allergan	0.899	12	Abbott	0.629	33
Astrazeneca	0.887	13	Daiichi Sankyo	0.621	34
Regeneron	0.858	14	Eisai	0.604	35
Merck & Company	0.852	15	Sanofi	0.594	36
Biogen	0.843	16	Otsuka	0.592	37
CSPC	0.804	17	Medtronic	0.561	38
Astellas	0.798	18	Novartis	0.538	39
Mylan	0.797	19	Bayer	0.503	40
Merck	0.775	20	DSM	0.460	41
H Lundbeck	0.775	21			

[a]The weight is rounded to 3 decimal places, the top three in their rankings based on the original scores which are not equal to 1

efficient PMNEs in both stages. The other PMNEs could reference Alfresa as a benchmark for a firm achieving high-performance improvement in both stages.

4.3.2 Compare ranking methods

Unlike traditional DEA, the TOPSIS-DEA and Game cross-efficiency methods can also be used for ranking DMUs (Liang et al., 2008; Lim & Zhu, 2015; Rakhshan, 2017)The advantages of TOPSIS-DEA compared to other ranking methods is its high flexibility and feasibility (Lim & Zhu, 2015; Rakhshan, 2017). However, this method can not be simultaneously performed on a two-stage full model. Liang et al. (2008) proposed a game cross-efficiency method to address the non-uniqueness of cross-efficiency scores. The advantage of the game the cross-efficiency method as compared with existing approaches is it takes both competition and cooperation relationships among DMUs into consideration. Moreover, the game cross-efficiency method considers peer appraisal by taking interaction among the DMUs into account.

To see the differences among three ranking methods including Game cross-efficiency, TOPSIS, and rough set, we performed Spearman rank-order correlation analysis. This nonparametric statistical approach is applied to measure the strength and direction of the

Table 9 Spearman rank-order correlation analyses

	Game cross	TOPSIS DEA	Rough set
Stage 1—R&D efficiency			
Game cross	1.000		
TOPSIS DEA	0.537***	1.000	
Rough set	0.810***	0.109	1.000
Stage 2—Business performance			
Game cross	1.000		
TOPSIS DEA	0.004	1.000	
Rough set	0.676***	0.380**	1.000

***, ** and * denote correlation is significant at the 1%, 5% and 10% level (2-tailed), respectively

monotonic association between two ranked variables (Lu et al., 2019). Firstly, Table 9 indicates that the rough set-based ranking approach is significantly and highly correlated with the Game cross-efficiency method of obtained DEA scores in stage 1 (coefficient = 0.810, p-value < 0.01) and stage 2 (coefficient = 0.676, p-value < 0.01). Our results show that the two ranking methods are adjacent. Rough set-based ranking method is preferable over the other methods such as Game cross-efficiency-based ranking method because rough set theory considers the impacts of the condition attribute on the sensitivity of inclusion/exclusion inputs, intermediates, and outputs. Secondly, the rough set-based ranking method has a significant correlation with the TOPSIS raking method of obtained DEA scores in stage 2 (coefficient = 0.380, p-value < 0.05). However, the correlation between the two methods is not significant in stage 1. The results indicate that two approaches (TOPSIS and rough set-based ranking method) are inconsistent. Wang and Luo (2006) suggested that the TOPSIS method is effectively used for distinguishing efficient DMUs. However, this method only enables ranking firms with the same efficiency score which is unfinished rankings while the rough set-based ranking approach examines all DMUs with considerations of different inputs, intermediates, and outputs combinations. Moreover, the TOPSIS method is sensitive to extreme values and this method cannot be simultaneously performed on full a two-stage model. Thus, the TOPSIS method must be implemented separately at each stage while the rough set approach can be performed simultaneously and thus prevents errors in estimation.

5 Conclusion

This study measures the firm performance of 41 PMNEs from a two-stage perspective, namely R&D efficiency and business performance, by integrating a two-stage network DEA and SOCP technique. Moreover, this study integrates the DEA approach and rough set theory to rank PMNEs. The findings of this research can serve as a reference for managers of PMNEs in their decision-making process. Besides, we examine differences in the ESG scores of the PMNEs among different geographic regions (America, Asia, and Europe). This acts as a guide for investors, managers, and other stakeholders when attempting to move their ESG initiatives further.

R&D performances in the operation of the observed PMNEs are not attracting enough attention. Alfresa Holdings Corporation is the only efficient PMNE for both R&D efficiency

and business performance. North America is significantly the best (worst) region in terms of business performance (R&D efficiency) while Europe is significantly the best (worst) region in terms of R&D efficiency (business performance). From the perspective of ESG performance, European PMNEs significantly have better environmental and social performance than other regions whereas they are the worst concerning governance performance.

Results from the rough set-based ranking approach indicate that most of the PMNEs that have a high rank in the first stage will get a low rank in the second stage. The exception is Alfresa Holdings Corporation, which performs well in both stages and hence can be considered as a benchmark for other PMNEs to reference and improve their performance across the two stages. Differences among three ranking methods including Game cross-efficiency, TOPSIS, and rough set is also compared in the present study. The results indicate that the rough set-based ranking method is consistent with Game cross-efficiency while it is inconsistent with TOPSIS.

As noted, this study uses MEA in a two-stage network DEA model with the SOCP technique to overcome: a requirement to predetermine weights across the two stages, the nonlinearity problem, the requirement for inputs of the second stage to be outputs from the first stage and that of VRS. A possible direction for future research to pursue is the implementation of this modelling approach to assess multinational enterprises in other industries. Secondly, the multiple objectives of evaluating PMNEs can serve as a reference for future studies. Although our study involves multiple factors such as ESG, future research may view the performance of PMNEs from different perspectives to obtain alternative analysis results.

Appendices

Appendix A: R&D efficiency scores of the 8 different combinations

PMNEs	M1	M2	M3	EX1	EX2	EX3	Y1	Y2	Ranking
DSM	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Bayer	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Alfresa	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Medtronic	1.000	1.000	0.474	1.000	0.927	1.000	0.932	1.000	0.916
Novartis	0.381	0.936	0.936	0.936	0.936	0.936	0.936	0.936	0.878
Piramal	0.402	0.818	0.818	0.818	0.818	0.818	0.818	0.818	0.774
Roche	0.470	0.802	0.802	0.802	0.802	0.802	0.802	0.802	0.767
Abbvie	0.068	0.713	0.713	0.713	0.713	0.713	0.713	0.713	0.645
Biogen	0.051	0.630	0.630	0.630	0.630	0.630	0.630	0.630	0.570
Amgen	0.058	0.596	0.596	0.596	0.596	0.596	0.596	0.596	0.540
Zoetis	0.212	0.383	0.383	0.383	0.383	0.383	0.383	0.383	0.365
Sanofi	0.339	0.352	0.354	0.352	0.352	0.353	0.352	0.350	0.350
Ipsen	0.241	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.346
CSL	0.093	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.264
H Lundbeck	0.179	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.262
Abbott	0.045	0.257	0.257	0.257	0.296	0.257	0.296	0.257	0.244

PMNEs	M1	M2	M3	EX1	EX2	EX3	Y1	Y2	Ranking
Eisai	0.084	0.259	0.259	0.259	0.259	0.259	0.259	0.259	0.240
Shionogi	0.135	0.251	0.251	0.251	0.251	0.251	0.251	0.251	0.239
CSPC	0.264	0.246	0.246	0.246	0.224	0.246	0.225	0.189	0.235
Incyte	0.104	0.242	0.242	0.242	0.242	0.242	0.242	0.242	0.227
Grifols	0.194	0.231	0.231	0.231	0.231	0.231	0.231	0.231	0.227
Pfizer	0.029	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.187
Allergan	0.128	0.190	0.190	0.190	0.190	0.187	0.190	0.187	0.183
Regeneron	0.027	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.160
Johnson & Johnson	0.164	0.164	0.060	0.164	0.164	0.164	0.164	0.164	0.151
UCB	0.094	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.149
Novo Nordisk	0.067	0.158	0.158	0.158	0.158	0.158	0.158	0.158	0.149
Alexion	0.022	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.143
Daiichi Sankyo	0.067	0.126	0.126	0.126	0.126	0.126	0.126	0.126	0.120
Otsuka	0.133	0.122	0.103	0.122	0.113	0.119	0.103	0.125	0.117
Vertex	0.041	0.121	0.121	0.121	0.121	0.121	0.121	0.121	0.113
Celltrion	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
Mckesson	0.095	0.095	0.068	0.095	0.095	0.095	0.069	0.095	0.089
Astellas	0.043	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.083
Mylan	0.065	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.073
Takeda	0.032	0.055	0.055	0.055	0.055	0.055	0.055	0.055	0.052
Astrazeneca	0.032	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.051
Eli Lilly	0.041	0.044	0.044	0.044	0.044	0.044	0.044	0.048	0.044
Teva	0.015	0.031	0.031	0.031	0.034	0.031	0.040	0.062	0.035
Merck	0.012	0.013	0.013	0.013	0.024	0.013	0.024	0.074	0.023
Merck & Company	0.018	0.014	0.014	0.014	0.014	0.014	0.014	0.048	0.019
Average	0.208	0.336	0.320	0.336	0.335	0.336	0.334	0.338	

Column M1 indicates the efficiency scores obtained after excluding patent citation
Column M2 indicates the efficiency scores obtained after excluding patent application
Column M3 indicates the efficiency scores obtained after excluding granted patent
Column EX1 indicates the efficiency scores obtained after excluding employees
Column EX2 indicates the efficiency scores obtained after excluding operating expenses
Column EX3 indicates the efficiency scores obtained after excluding property, plant & equipment
Column Y1 indicates the efficiency scores obtained after excluding revenues
Column Y2 indicates the efficiency scores obtained after excluding market value

Appendix B: Business performance scores of the 8 different combinations

PMNEs	M1	M2	M3	EX1	EX2	EX3	Y1	Y2	Ranking
Incyte	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Celltrion	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Alfresa	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mckesson	1.000	1.000	1.000	1.000	1.000	1.000	0.974	1.000	0.998
Vertex	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.633	0.974
Alexion	1.000	1.000	1.000	1.000	1.000	1.000	0.853	0.660	0.966
Piramal	1.000	1.000	1.000	1.000	1.000	0.780	1.000	1.000	0.964
Johnson & Johnson	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.175	0.942
Novo Nordisk	1.000	1.000	1.000	1.000	0.978	1.000	0.978	0.156	0.937
Amgen	1.000	1.000	1.000	0.795	1.000	1.000	1.000	0.300	0.912
Abbvie	1.000	1.000	1.000	1.000	1.000	0.770	1.000	0.236	0.909
Allergan	0.901	1.000	1.000	1.000	1.000	0.688	1.000	0.300	0.899
Astrazeneca	0.891	0.958	0.958	0.799	0.958	0.958	0.809	0.524	0.887
Regeneron	0.986	0.940	0.940	0.839	0.773	0.940	0.773	0.430	0.858
Merck & Company	0.814	0.936	0.936	0.923	0.758	0.936	0.715	0.221	0.852
Biogen	1.000	0.891	0.891	0.812	0.893	0.891	0.893	0.415	0.843
CSPC	0.759	0.848	0.848	0.848	0.646	0.848	0.642	0.695	0.804
Astellas	0.843	0.930	0.930	0.929	0.462	0.851	0.437	0.335	0.798
Mylan	0.879	0.926	0.926	0.926	0.484	0.874	0.473	0.224	0.797
Merck	0.636	0.833	0.837	0.841	0.587	0.996	0.521	0.238	0.775
H Lundbeck	0.847	0.840	0.840	0.835	0.711	0.645	0.675	0.711	0.775
Teva	0.892	0.919	0.919	0.919	0.315	0.919	0.268	0.178	0.767
Shionogi	0.815	0.849	0.849	0.826	0.601	0.756	0.573	0.559	0.767
Zoetis	0.767	0.830	0.830	0.819	0.654	0.793	0.652	0.348	0.759
Ipsen	0.807	0.813	0.813	0.789	0.680	0.682	0.641	0.693	0.754
Eli Lilly	0.749	0.845	0.845	0.821	0.560	0.845	0.553	0.208	0.749
CSL	0.791	0.807	0.807	0.807	0.631	0.807	0.631	0.221	0.738
Pfizer	0.997	0.791	0.791	0.791	0.713	0.791	0.714	0.165	0.736
Grifols	0.771	0.840	0.840	0.840	0.418	0.840	0.415	0.261	0.731
UCB	0.813	0.837	0.837	0.811	0.463	0.721	0.482	0.463	0.728
Roche	0.771	0.699	0.699	0.699	0.615	0.699	0.615	0.146	0.647
Takeda	0.660	0.767	0.767	0.747	0.302	0.756	0.264	0.208	0.645
Abbott	0.845	0.711	0.711	0.711	0.464	0.709	0.463	0.106	0.629
Daiichi Sankyo	0.675	0.745	0.745	0.743	0.251	0.705	0.215	0.251	0.621
Eisai	0.719	0.694	0.694	0.685	0.385	0.612	0.373	0.350	0.604
Sanofi	0.702	0.701	0.657	0.701	0.364	0.688	0.361	0.105	0.594
Otsuka	0.618	0.706	0.734	0.706	0.220	0.672	0.228	0.178	0.592

PMNEs	M1	M2	M3	EX1	EX2	EX3	Y1	Y2	Ranking
Medtronic	0.603	0.608	0.638	0.608	0.544	0.570	0.539	0.092	0.561
Novartis	0.697	0.599	0.599	0.599	0.430	0.599	0.424	0.103	0.538
Bayer	0.595	0.602	0.582	0.602	0.244	0.592	0.223	0.105	0.503
DSM	0.430	0.562	0.559	0.549	0.146	0.561	0.116	0.146	0.460
Average	0.836	0.854	0.854	0.837	0.665	0.817	0.646	0.394	

Column M1 indicates the efficiency scores obtained after excluding patent citation
Column M2 indicates the efficiency scores obtained after excluding patent application
Column M3 indicates the efficiency scores obtained after excluding granted patent
Column EX1 indicates the efficiency scores obtained after excluding employees
Column EX2 indicates the efficiency scores obtained after excluding operating expenses
Column EX3 indicates the efficiency scores obtained after excluding property, plant & equipment
Column Y1 indicates the efficiency scores obtained after excluding revenues
Column Y2 indicates the efficiency scores obtained after excluding market value

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