Financial Performance Drivers in BRICS Healthcare Companies: Locally Estimated Scatterplot Smoothing Partial Utility Functions

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Abstract: The Healthcare sector is increasing in importance and relative size in BRICS countries (Brazil, Russia, India, China, South Africa). Despite BRICS relevance, the financial performance of their healthcare companies has been scarcely studied. This research fills this literature gap not only by focusing on the impacts of such diverse business environments on the financial performance of healthcare providers but also by proposing a novel approach to estimate an overall financial performance index based on weighted additive utility functions given a set of financial performance criteria. Precisely, bootstrapped Singular Value Decomposition (SVD) is the cornerstone for identifying an orthogonal base of rotated financial performance criteria, upon which partial utility functions (PUFs) are estimated using LOESS (locally estimated scatterplot smoothing) polynomial regression. A compromise weighting scheme between singular values and quadratic programming results for minimal covariance and joint entropy matrices of residuals was used for summing up the PUFs. Results indicate that the values of financial performance range between 0.7 and 0.85. We further find that current assets, level of debt and liability, the company's Tobin Q are related to the financial performance. Besides, business freedom, government integrity, tax burden, monetary freedom and government spending are also the determinants of financial performance.

Keywords: Multiple criteria analysis; financial health index; utility functions; SVD; loess estimation

1. Introduction

Based on the data provided by the world bank, the life expectancy in BRICS over the period 2009-2018 kept increasing with China reaching the highest age by the end of 2018, which was 76.7 while comparing with European countries such as the United Kingdom or the United State, it was much lower. The life expectancy in the United States over the same period was over 78 on average, while the one for the United Kingdom was even higher with more than 80 on average. Life expectancy is affected by many factors, among which the natural environment plays a key role. Fine particulate matter (PM2.5) is an air pollutant that significantly influences people health in a negative way which is derived from various economic activities. Based on the data provided by the World Bank, over the period 2010-2017, the mean annual exposure of PM2.5 air pollution among BRICS was much higher than the one of the United Kingdom and United State. The data shows among BRICS, Brazil has the lowest level of pollution, with the level of mean exposure of PM2.5 ranged between 12 and 16 micrograms per cubic meter. In comparison, the annual mean exposure of PM2.5 in the United Kingdom over the same period ranged between 10-13 while for the United States, it ranged between 7.4 and 9.7.

There would a dilemma between economic development and preservation of the natural environment in particular for the developing countries like BRICS with a relatively lower level of technological advancement and lower ability of research and innovation. Purely pursuing economic development with less consideration or less complete mechanism in protecting the natural environment will significantly and negatively affect people’s life from the perspective of increasing the possibility of illness and reduce life expectancy. One of the possible solutions to mitigate the negative influence of excessive economic activities on people’s health is to provide a good healthcare system. In other words, a good healthcare system will not only be able to meet the demand of the citizen for healthcare products and services but also to make sure that the citizen will be able to get access to this at a reasonable price level. How to achieve this system would be a priority for the government and health regulatory authorities. The availability of healthcare-related products or services as well as the price level will be determined by the performance of the healthcare organizations, a higher level of performance, in particular, from the financial perspective, will provide a higher ability to the healthcare organizations to increase the health equipment, increase the amount of staff or even expand their operations through opening up additional locations, while a higher level of performance will also enable the healthcare organization to lower down the price level of health-related products and services, which will not only benefit to the citizen but eventually contribute to the establishment of a better healthcare system.

Not only the pollution issues in BRICS ask for improvement in the financial performance of the healthcare industry, but also some other social and macroeconomic issues request the healthcare industry to be financially strong and resistant. One of the challenges faced by BRICs is inequality. Based on Oxfam, people living in the rural area of Africa, India and China are poorer than the urban counterparts, besides, the people living in the rural area is excluded from the public benefits such as health insurance. Based on these circumstances, the stronger position of the financial performance of healthcare companies would be able to relieve this inequality related to the access to healthcare services between the people in the rural area and urban area. Also, poverty is another challenge faced by BRICS. Based on the data provided by the World banks, among the five countries of BRICS, Russia had the lowest poverty headcount ratio at 5.50 USD a day in 2018 which was 3.7%, in comparison, the United States had a ratio of around 1.7% and the United Kingdom had the ratios ranged between 0.5 and 0.7 between 2009-2016. This data shows that a larger amount of people in BRICS still faced difficulties in meeting the basic demand for their daily life, this posed a very big threat to their health conditions. This scenario can be alleviated to a more or less extent by a good healthcare system and in particular, the higher performance of healthcare companies from the finance perspective would be able to provide healthcare-related products and services to the poor people at the lowest price possible or probably free healthcare.

Hence, this research departs from previous studies by proposing a novel stochastic-robust methodology to compute an overall financial performance index based on LOESS estimation of the PUFs inherent to each rotated criterion obtained from SVD. This approach is stochastic because it relies on the bootstrapping of the original decision-matrix, where columns comprise different financial performance criteria and lines represent different healthcare companies of the BRICS countries. On the other hand, this approach is robust because alternative rescaling of rotated criteria is considered using quadratic programming, yielding an overall utility function that not only takes into account the relative importance as represented by their singular values, but also the optimal weights for minimal covariance and joint entropy matrices of estimated PUF residuals using LOESS. Results indicate that the values of financial performance range between 0.7 and 0.85, indicating that the financial performance of the BRICS healthcare companies is not low although there is still room for further improvement. We further find that both the company-specific factors including current assets, level of debt and liability, the company's Tobin Q are significantly related to the financial performance. Besides, various macroeconomic indicators such as business freedom, government integrity, tax burden, monetary freedom as well as government spending are the determinants of the financial performance of healthcare companies in BRICS.

This paper is structured in five more sections. Section 2 deals with the healthcare sector in BRICS countries, their history, current statuses, and future perspectives/challenges. Section 3 presents the literature review, indicating the research gap based on previous studies that addressed the financial performance issues of healthcare companies: locus of research, main methods used, and major conclusions reached. Section 4 is devoted to the description of the dataset and a more detailed discussion on the novel approach developed here. Section 5 treats the analysis and discussion of results, while Section 6 concludes the paper, presenting policy and managerial implications, research limitations, as well as direction for future venues.

2. Contextual Setting

Together, the BRICS countries can be characterized for almost 25 per cent of the world's GDP and 40 per cent of the world's population. Worldwide, some policymakers consider BRICS as a changing wave for the global health frontier (Harmer & Fleck, 2014). Besides their combined importance, BRICS countries have also been mainly differentiating for their similarities in the state of economic transformation and economic development since all of these countries are members of G20 (Romaniuk, Poznańska, Brukało, & Holecki, 2020). They all have a healthcare scheme of both public and private ownership. The nature of problems in the healthcare systems among these countries also seems similar- shortage in doctor and nurses, space limitation and underfinancing. However, the main characteristics of the healthcare system (e.g., mortality rate, universal health coverage, infant mortality rate, etc.) in BRICS countries are different (Pant, 2013).

Brazil, for instance, serves its total citizen from three levels (municipal, state and federal) under universal health protection in light of the federal constitution of 1988 (Nunes et al., 2016). Compared to the Brazilian healthcare system, the Russian healthcare system is different in terms of financing and health service coverage. Under the provision of compulsory health insurance, this system provides basic healthcare to all citizens. Additionally, Russia approves private healthcare services through voluntary health insurance. In terms of ownership, 68% of ownership remains in the state. Similar to this, India also operates a mix of both public and private ownership among the healthcare institutions through compulsory social insurance (Prinja et al., 2017). Besides its healthcare insurance, the citizens of India must spend most of their health care costs on the own. Thus, compared to the other four countries in BRICS, India stood the first for most privatized healthcare (Panda & Thakur, 2016). The government of China has been taking several initiatives for ensuring wide access to healthcare for the citizens (Romaniuk et al., 2020). However, recently, China has been shifting to privatization of its healthcare system (Zhai et al., 2017). A very similar trend in shifting ownership of the healthcare system from public to private is also available in the South African healthcare system (Maphumulo & Bhengu, 2019).

Among these five countries, the basic problems and challenges among the healthcare institutions are different based on the above-explained context. Yet, considering the economic development and geographical context, these countries seem close. A timely research question, however, reveals from this context that whether the performance of the healthcare systems among these countries is the same. Analyzing the basic features of these countries may not be suitable to conclude how the healthcare systems are performing. Moreover, such similarities among the countries may not explain what the drivers of the performances of these healthcare systems are. This study, for the first time, not only explains a comparative performance among the healthcare systems in BRICS countries but only examines the drivers of these healthcare systems.

3. Literature Review

There are several empirical research studies investigating the financial performance of healthcare organizations over the last two decades, with plenty of studies focused on the hospitals. The evaluation of the financial performance of hospitals was initiated by Ozcan and McCue (1996) who used a non-parametric Data Envelopment Analysis (DEA) to obtain a financial performance index. The index was based on four maximizing financial ratios namely return on assets, operating cash flow per bed, operating margin and total assets turnover ratio. The application of DEA in estimating performance in the healthcare/hospital sector has been witnessed by several research studies over the last two decades (Chen et al., 2005; Butler and Li, 2005; Shwartz et al., 2016; Lindlbauer et al., 2016). Instead of using the operational research method such as DEA, Chan et al. (1999) use the accounting ratios to measure the financial performance of rural hospitals in consortia including total operating profit, cost per adjusted admission, and revenue per adjusted admission. The study considered several potential determinants such as degree of group formalization, group asymmetry, affiliation with other consortium groups, individual economic development as well as hospital characteristics. The results do not find any clear evidence regarding the impact of group economic environment, however, a curvilinear relationship between group size and financial performance was found.

The investigation of the financial performance of hospitals was also attempted by the literature studies from the perspective of strategic management and corporate governance. The effect of downsizing on financial performance was examined by Chadwick et al. (2004). The cash margin was used as the main financial performance indicator. The financial performance was significantly affected by several factors including 1) the consideration of staff morale and welfare during downsizing; 2) advance notice of layoff; 3) provision of extended insurance to lay-off employees; 4) planned redesign of work structure. Using excess income margin as the financial performance indicator, Eldenburg et al. (2004) evaluate the relationship between corporate governance and the financial performance of hospitals. The results show that the board and CEO turnover are related to poor financial performance.

Besides the above studies, attempts were also made to address the relationship between financial performance and hospital operation. In particular, Bazzoli et al. (2008) evaluate the relationship between financial performance and quality of care. Two financial performance indicators are used including operating margin and a broader profitability indicator capturing both the operating and non-operating income. The findings show that there is a level of relationship between the two, while it seems that the significance of the relationship was not as strong as shown in the previous studies. This issue was also investigated by Park and Werner (2011).

In addition to the investigation of financial performance from the corporate governance perspective, an effort has also been made to investigate the relationship between human resource practice and financial performance (Akdere, 2009). Based on two different financial performance indicators namely, operating margin and net margin, the findings show that knowledge management, strategic management, process management and employee satisfaction are found to significantly affect financial performance.

Using three financial indicators to measure performance including net patient revenue, total operating cost as well as margin, Carey et al. (2011) investigate the relationship between hospital competition and financial performance. The findings suggest that there is a significant and negative impact of competition on hospital profits. Similar research was also conducted by Andritsos and Aflaki (2015). Reiter et al. (2012) use three different financial performance indicators including operating margin, total operating expenses per adjusted patient day, as well as inpatient operating expenses per discharge, to investigate the effect of the minimum nursing staff ratio. The hospitals were grouped into quartiles based on the nursing staff levels with the lowest quartile indicating the lowest staffing. The findings show that operating margins declined significantly in quartiles 2 and 3 while operating expenses increased significantly in quartiles 1, 2 and 3. Finally, Dobrzykowski et al. (2016) use revenue per discharge as the main financial performance indicator and examine the relationship between lean orientation, internal integration, patient safety, and financial performance. The findings show that a comprehensive lean orientation has an indirect impact on financial performance through internal integration.

Besides the use of traditional accounting ratios as well as the operational research method such as DEA, few studies measured the financial performance of the healthcare organization under the balanced scorecard methodology under the multiple-criteria approach and (Grigoroudis et al., 2012) and fuzzy linguistic approach (Lin et al., 2013). The balanced scorecard methodology benefits from the advantages of including in the evaluation system not only the most important financial performance indicators but also a series of non-financial performance indicators reflecting the quality of services provided, the satisfaction of internal and external customers, self-improvement system of the organization as well as the ability of the organization to adapt and change.

Using net patient revenue as the main financial performance indicator, Devaraj et al. (2013) investigate the influence of information technology and patient flow. The findings suggest that the revenue can be improved by the hospitals with Information technology associated with swift and even patient flow, the study further shows that improvement in the financial performance is not at the expenses of quality of patient care. The investigation related to the impact of Information technology on financial performance is also conducted by Smith et al., (2013).

4. Methodology

Several datasets from different data sources are collected for this study. The financial information of different healthcare institutions and country information (e.g., business freedom, labor freedom, monetary freedom, trade freedom) are collected from the Thomson Reuters database from 2009 to 2019 (Table 1). The current health expenditure[1] (% of GDP), current health expenditure per capita[2] (current US$), and domestic general government health expenditure[3] (% of GDP) are collected from World Health Organization Global Health Expenditure database[4]. Data related to GDP per capita (trillion US$), GDP per capita growth (annual %), GNI (current US$) and GNI growth (annual %) are collected from World Bank national accounts data and OECD National Accounts data files.

[1] Level of current health expenditure expressed as a percentage of GDP. Estimates of current health expenditures include healthcare goods and services consumed during each year. This indicator does not include capital health expenditures such as buildings, machinery, IT and stocks of vaccines for emergency or outbreaks.
[2] Public expenditure on health from domestic sources as a share of the economy as measured by GDP.
[3] Current expenditures on health per capita in current US dollars. Estimates of current health expenditures include healthcare goods and services consumed during each year.
[4] http://apps.who.int/nha/database

Table 1. Descriptive statistics summary.

Positive and Negative criteria	**Max**	**Min**	**Mean**	**SD**	**CV**	**Skewness**	**Kurtosis**
TotalCurrentAssets(billion US$)	17.24	17.24	0.96	2	0.48	2.82	7.64
TotalAssetsReported(billion US$)	19.13	19.13	0.94	2	0.50	3.29	12.39
TotalDebt(billion US$)	10.26	10.26	1.31	2	0.55	2.02	3.07
TotalLiabilities(billion US$)	17.14	17.14	1.11	2	0.50	2.42	5.24
RetainedEarnings(billion US$)	10.00	10.00	0.74	2	0.31	1.21	5.85
TotalEquity(billion US$)	9.99	9.99	0.86	2	0.48	3.02	9.00
TotalRevenue(billion US$)	21.07	21.07	0.83	2	0.44	3.50	14.75
NetIncomeAfterTaxes(billion US$)	9.99	9.99	1.41	3	0.46	0.76	1.43
BasicNormalizedEps(billion US$)	9.99	9.99	1.41	3	0.46	0.76	1.43
CashFromOperatingAct(billion US$)	9.99	9.99	1.16	3	0.37	0.56	1.87
CashFromInvestingAct(billion US$)	9.85	9.85	-1.25	3	-0.43	-0.70	2.09
CashFromFinancingAct(billion US$)	9.93	9.93	-0.33	3	-0.10	-0.18	1.87
FreeCashFlow(billion US$)	10.00	10.00	0.43	3	0.12	0.05	1.33
Business environment variables	Max	Min	Mean	SD	CV	Skewness	Kurtosis
EQCountryListRank	100.00	1.00	44.91	26.71	1.68	0.26	-0.70
ZScoreManufacturingWeights	2510.20	-29.58	10.63	38.95	0.27	54.40	3453.08
ZScoreNonManufacturingWeights	4396.46	-71.29	18.84	68.46	0.28	53.82	3402.72
property rights	55.00	20.00	31.84	15.03	2.12	0.57	-1.63

government integrity	43.00	21.00	35.82	2.60	13.78	-1.55	6.51
tax burden	86.90	65.80	72.89	3.71	19.67	1.00	-0.12
government spending	88.90	47.00	78.70	6.58	11.97	-1.61	5.65
business freedom	76.30	35.50	47.96	6.27	7.65	-0.25	0.83
labor freedom	74.20	47.80	60.72	6.11	9.94	0.31	0.57
monetary freedom	77.20	62.60	70.61	3.53	19.99	-0.65	-0.91
trade freedom	77.40	51.00	70.20	4.82	14.56	-1.79	4.58
investment freedom	55.00	20.00	30.33	5.41	5.61	1.01	3.27
financial freedom	60.00	30.00	34.02	5.64	6.03	1.37	2.56
tobinq	52.43	0.00	2.42	2.73	0.89	5.97	77.64
Current health expenditure (% of GDP)	9.47	3.25	4.38	0.83	5.28	2.19	10.52
Current health expenditure per capita (current US$)	1025.49	38.41	279.29	181.88	1.54	0.59	1.08
Domestic general government health expenditure (% of GDP)	4.24	0.86	2.10	0.85	2.47	-0.35	-1.24
GDP per capita (trillion US$)	15974.64	1101.96	5627.06	3363.59	1.67	0.05	-1.26
GDP per capita growth (annual %)	10.10	-7.83	6.36	1.91	3.33	-1.76	9.58
GNI (current US$)	14.31	1.18	7.20	4.57	1.57	0.07	-1.54
GNI growth (annual %)	10.34	-7.92	7.15	1.79	3.99	-2.57	14.59

4.1. Weighted-Additive PUFs

Very often, a utility function expresses the preferences of a decision-maker in terms of how much benefit is obtained from using a given product on service (Chakrabarti and Roy, 2010). While this research does not deal exactly with decision-makers preferences in terms of consumption, we could conceptualize utility function here as the underlying or intrinsic benefit, in terms of overall financial performance, captured by different healthcare companies (or alternatives) when targeting the optimization of a particular financial performance (or criteria), that could be either positive or negative.

Utility functions are well-known multicriteria decision-making methods (Wu and Tiao, 2018). The approach is the form most simply and easily understood by decision-makers since it does not require any stronger restrictions than the aggregation formula (Pavan and Todeschini, 2009). Typically, they start with data normalization between 0-1 conducted locally at each criterion, taking simply the best and worst of the available alternatives.

Let's consider a set of d healthcare companies[5], each one of them formed by o positive financial criteria to performance - $pos_{d,o}$ - and i negative criteria to performance - $neg_{d,i}$ -, where $d = \{1..n\}$, $o = \{1..m\}$, $i = \{1..s\}$, **pos** and **neg** are, respectively, positive and negative criteria matrices with dimensions nxm and nxs. The maximal utility value attainable for all d healthcare companies for each negative criteria i is given by max(neg_i) while the maximal utility value for each positive criteria o is given by max(pos_o), for all healthcare company d. These maximal utility values are the cornerstones for computing the normalized values for each negative criterion i and positive criterion o at each healthcare company, such as:

$x_{d,o} = (pos_{d,o} - \min(pos_o))/(\max(pos_o)-\min(pos_o))$, $x_{d,o}$ ranges between 0 and 1 for all o and d (1)

$x_{d,i} = (\max(neg_i) - neg_{d,i})/(\max(neg_i)-\min(neg_i))$, $x_{d,i}$ ranges between 0 and 1 for all o and d (2)

where $x_{d,o}$ is the normalized positive criterion o at healthcare company d, while $x_{d,i}$ is normalized negative criterion i at healthcare company d. One can see that maximal values for positive criteria would correspond to a normalized value of 1. Conversely, maximal values for negative criteria would correspond to a normalized value of zero, thus allowing to treat both sets of criteria simultaneously in a normalized decision-making matrix **x** with dimensions nx(m+s).

Let´s also consider **w** a weight column-vector assigned to the $c = \{1..k, k = m+s\}$ criteria displayed in **x**. The overall utility value V for each alternative d can be computed as:

[5] *d* standing for DMU or Decision-Making Unit.

$V_d = \sum_{c=1}^{k} x_{d,c} * w_c$, where $\sum_{c=1}^{k} w_c = 1.$ (3)

Besides, the weighted normalized decision-matrix **V** can be represented as:

$$\mathbf{V} = \begin{bmatrix} x_{1,1} * w_1 & \cdots & x_{1,k} * w_k \\ \vdots & \ddots & \vdots \\ x_{d,1} * w_1 & \cdots & x_{d,k} * w_k \end{bmatrix} \quad (4)$$

where each of the *k* sub-column vectors in **V** represent the partial weighted utility vector for all *d* healthcare companies with respect to a given criterion *c*. This decision-making matrix representation of the weighted normalized criteria is of cornerstone importance for the interpretation of the SVD results (Nilashi et al., 2014), as discussed next section.

4.2. SVD

In this research, SVD takes a rectangular decision-making matrix **V** of financial performance criteria for each healthcare company and decomposes it into three distinct components, given as (Alter et al., 2000; Greenberg, 2001):

$$\mathbf{V}_{nxk} = \mathbf{C}_{nxn} * \mathbf{S}_{nxk} * \mathbf{L}^{\mathrm{T}}_{kxk} \quad (5)$$

While sometimes the interpretations of these components may not be straightforward (Zhang and Han, 2019), as regards this research, it follows that:

- **L** is the loading-factor matrix for the *k* novel rotated criteria; rotated criteria are determined as "internal regressions" based on original criteria (Wang et al., 2018).

S is the axis-scale matrix for the *k*-dimensional space defined by the rotated criteria in **L**; the elements of its principal diagonal are the singular values, which denote the relative intrinsic importance or weight of each rotated criteria (Akadiri et al., 2013). For many practical purposes, singular values can be assigned as a weight column vector **s** to **C** (Hu et al., 2017).

- **C** is the utility coefficient-matrix to be assigned to **x** (Bhaskara et al., 2020). It is formed by various sub-column vectors, each of them representing the rotation coefficients for the *d* original alternatives with respect to a given criteria *c* (Wu and Sun, 2013). It follows that the PUFs for all *d* alternatives (or healthcare companies) with respect to each criteria *c* are the column-vectors defined in the decision-matrix comprised by **Cx** (element-wise multiplication):

$$\mathbf{Cx} = \begin{bmatrix} c_{1,1} * x_{1,1} & \cdots & c_{1,n} * x_{1,n} \\ \vdots & \ddots & \vdots \\ c_{d,1} * x_{d,1} & \cdots & c_{d,n} * x_{d,n} \end{bmatrix} \quad (6)$$

As further discussed in the next section, LOESS estimation is used to model the relationships between $\mathbf{PUF}_{\boldsymbol{c}} = \boldsymbol{f}(\mathbf{x}_{\boldsymbol{c}})$ for all *c*, where $\mathbf{PUF}_{\boldsymbol{c}}$ and $\mathbf{x}_{\boldsymbol{c}}$ are the respective sub-column vectors defined for each criterion *c* in decision-matrices **Cx** and **x**, respectively.

4.3. LOESS

Local polynomial regression (Fox and Weisberg, 2018) or moving regression (Harrel, 2015) are generalizations of combined moving averages and polynomial regression (Garimella, 2017). LOESS is one of the most basic approaches of such kind, consisting of a non-parametric regression method that combine polynomial regression models (with degree 1 or 2) in a k-nearest-neighbor (k-nn) local search (where the coverage span of vicinity data is the parameter of interest). In this research, the LOESS residual sum-square vector for each criterion *c* ($\mathbf{R}_{\boldsymbol{c}}$) is given as:

$$\mathbf{R}_{\boldsymbol{c}} = \sum_{\boldsymbol{d}=\mathbf{1}}^{\boldsymbol{n}} (\mathbf{PUF}_{\boldsymbol{c}} - \mathbf{Ax}_{\boldsymbol{c}})^{\mathbf{T}} * \mathbf{w}_{\boldsymbol{d}}\,(\mathbf{x}_{\boldsymbol{c}}) * (\mathbf{PUF}_{\boldsymbol{c}} - \mathbf{Ax}_{\boldsymbol{c}}) \tag{7}$$

where **A** is a n+1 square matrix of coefficients related to the degree of the polynomial fit and $\mathbf{w}_{\boldsymbol{d}}$ is a Gaussian vector of weights for each alternative *d*, computed in terms of the mean and variance of the vicinity data span in the k-nn search.

4.4. Compromise weighting

Quadratic programming is further used to explore alternative criteria weighting schemes, differently from the vector of singular values, **ws**, obtained from the principal diagonal of **S** in eq. (5). Precisely, square covariance and join entropy matrices for the residuals computed in eq. (7) are subject to minimization given, respectively, optimal **wc** and **we** weight vectors. While minimal residual covariance may assure unbiased overall financial performance when summing up distinct partial utility functions for each criterion (Wang et al., 2017), minimal joint entropy is strictly related to maximal mutual information (Wu and Verdu, 2011), yielding the best combination of criteria from which it is possible to learn from one another in continuous improvement initiatives (Singh et al., 2007). Hence, it follows that:

<u>For minimal covariance square matrix of residuals ($\mathbf{Cov}(\mathbf{R_c})$)</u>

Minimize $\mathbf{0.5} * \mathbf{wc}^{\mathbf{T}} * \mathbf{Cov}(\mathbf{R_c}) * \mathbf{wc}$

Subject to:

$$\sum_{c=1}^{k} wc_c = 1 \tag{8}$$

$0 \leq wc_c \leq 1$ for all c

For minimal Joint Entropy square matrix of residuals ($\mathbf{E}(\mathbf{R_c})$)

Minimize $\mathbf{we^T} * \mathbf{E}(\mathbf{R_c}) * \mathbf{we}$

Subject to:

$\sum_{c=1}^{k} we_c = 1$ (9)

$0 \leq we_c \leq 1$ for all c

At last, the LOESS estimate for the overall rotated utility value *RUV* for each alternative *d*, based on compromise weights, can be computed as:

$$RUV_d = \sum_{c=1}^{k} \overbrace{x_{d,c} * a_{d,c}}^{LOESS\ estimate} * (wc_c + we_c + ws_c)/3 \qquad (10)$$

Where:

$\sum_{c=1}^{k} wc_c = 1$

$\sum_{c=1}^{k} we_c = 1$

$\sum_{c=1}^{k} ws_c = 1$

4.5. LOESS PUFs Based on Stochastic-Robust SVD

Table 2 synthesizes the pseudo-code implemented in R, which is available to readers upon request. The steps depicted in subsections 4.1 to 4.5 were subjected to 100 bootstrap replications, each of them departed from 100 line-resamples, without repetition, of the original decision-matrix **x**.

Table 2. Pseudo-code.

1) Normalize d matrix using equations (1) and (2)	
2) Compute Utility Value Matrix V following equation (4)	
3) for B from 1 to 100 do	
	3.1) Create Matrix V' sampling rows from V
	3.2) Evaluate SVD of V'
	3.3) Create Matrix Cx with equation (6)
	3.4) Compute LOESS following eq (7)
	3.5) Evaluate model (8) to find weights that minimize covariance matrix
	3.6) Evaluate model (9) to find weights that minimize joint entropy
	3.7) Find RUV values for criteria d following equation (10)
end do	

5. Analysis and Discussion of Results

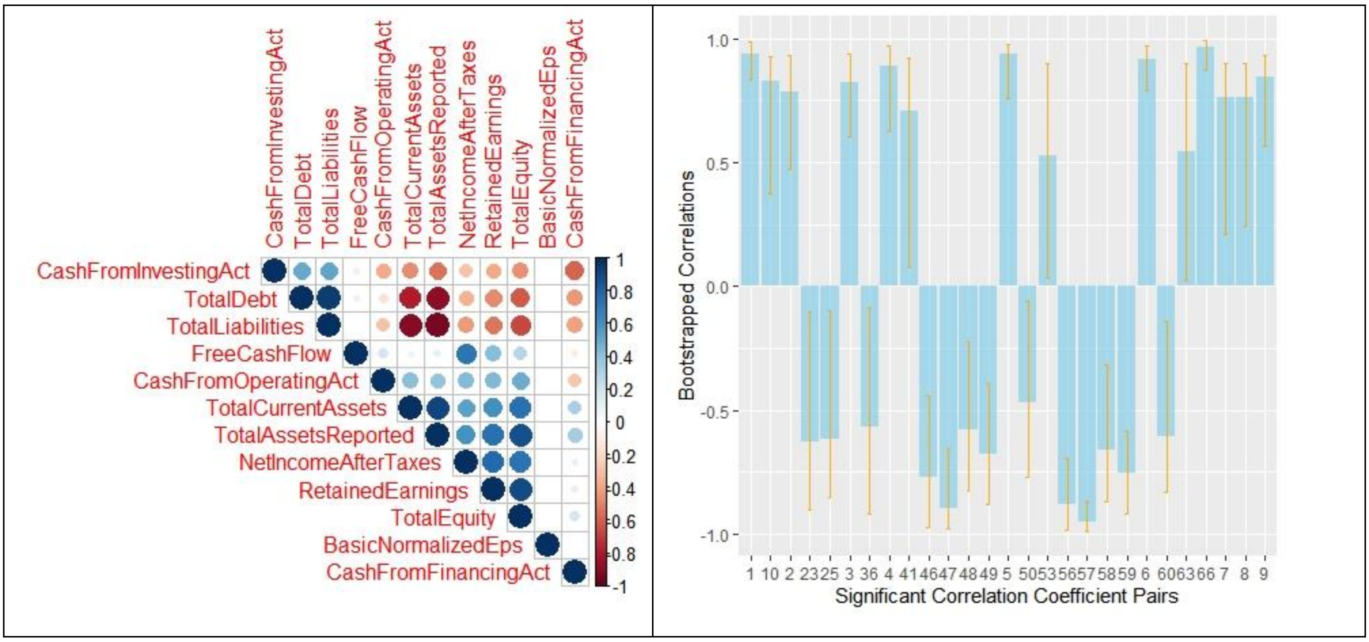

Fig. 1. Correlogram (left) and significant correlation pairs (right).

Correlation results for the original and the bootstrapped decision matrices are depicted in Fig. 1. While one can note that debt and liabilities are criteria strongly and negatively correlated to current assets, equity, and cash generation from financing; current assets appear to be the key criterion for sustaining overall financial performance in BRICS healthcare companies, given the significant correlation pair list as reported in Appendix 1. Current assets are significantly and positively correlated to equity, retained earnings, earning per share, cash generation, and net income. On the other hand, debt and liabilities appear to indirectly jeopardize the balance between cash generation from investing and financing, yielding smaller earning per shares and, therefore, impacting the overall financial performance. These results suggest that size, as proxied by assets, seems to be a necessary condition to face the undesirable effects of debts and liabilities in healthcare operations in BRICS countries, suggesting that, to some extent, economies of scale can sustain financial health under adverse financing conditions and cash generation due to demand volatility.

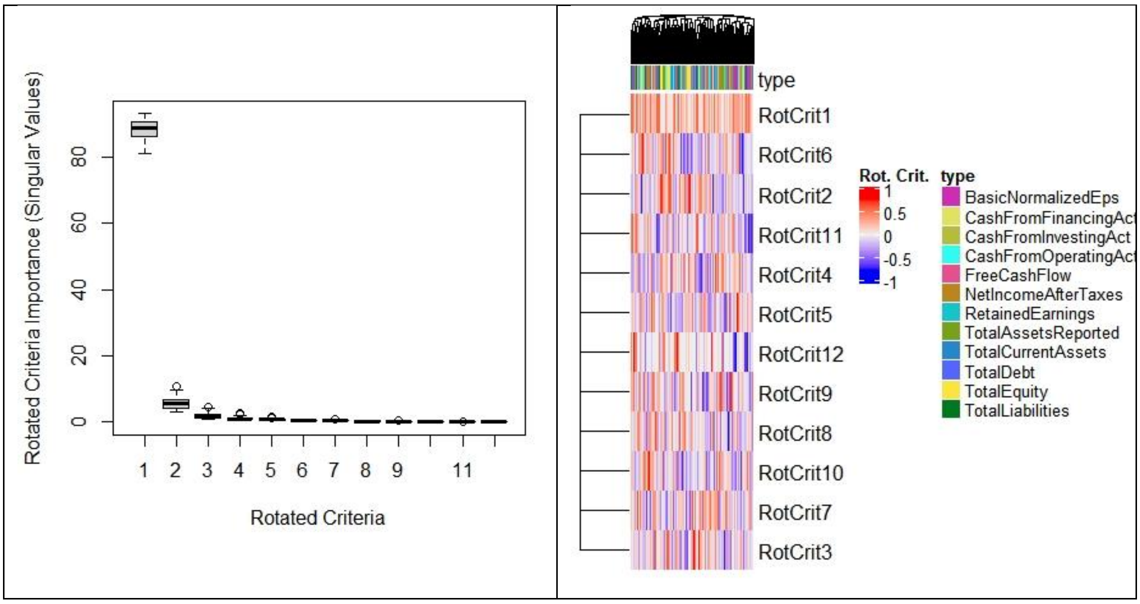

Fig 2. Bootstrapped results for the singular values (**S**, on the left) and respective factor loadings (**L**, on the right).

Results for the bootstrapped rotated criteria, as depicted in Fig. 2, also suggest an intricated relationship net between positive and negative criteria. One can easily see, for instance, that the most important rotated criteria accounts for more than 80% of the overall importance of the SVD and it is almost equally formed by the original criteria, what does not happen with the remainder rotated criteria, where weights vary substantially amongst original criteria. Notwithstanding the decaying importance of the remainder rotated criteria, they are also helpful in predicting the overall utility function to proxy financial health, as long as they reflect different trade-off balances among original criteria, which is reflected in the strongest contrasts (or expressions) in red and blue.

Hence, results for the quadratic programming solutions on the alternative weighting schemes for the rotated criteria – respectively based on minimal covariance and joint entropy matrices – are reported in Fig. 3 and Table 3. While rotated criteria 1 is still the most important, on average, the relative importance of the remainder rotated criteria substantially varied in comparison to those derived from SVD. These results suggest that both paths for either an unbiased computation of utility functions (minimal covariance matrix) or for exploiting learning approaches based on continuous improvement (where it is possible to learn about one criterion based on the other due to maximal mutual entropy) are distinct from the orthonormal rotated criteria base resulting from singular values.

Table 4 reports on the best average span values for the LOESS estimation for each rotated criterion. All average values ranged between 0.70 and 0.85, and an overall compromise average span value of 0.80 was adopted, altogether with a polynomial degree of order 1 when computing the overall financial performance – as proxied by such utility functions – based on the original decision-matrix and the compromise weighting depicted in Table 3.

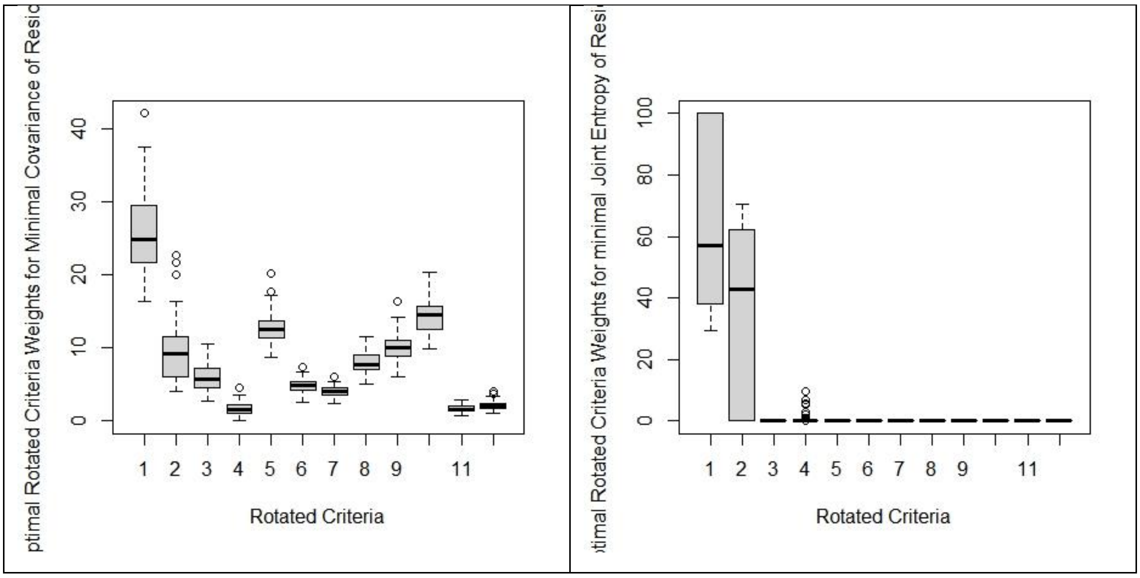

Fig. 3. Bootstrapped results for **wc** (left) and **we** (right) weight vectors.

Table 3. Compromise weights summary (Bootstrap averages)

Rotated Criteria	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Importance Weights (Singular Values)	88.47	5.74	1.85	1.15	0.81	0.60	0.46	0.33	0.24	0.18	0.12	0.04
Minimal Covar of Residuals (Minimal Bias)	25.37	9.51	5.87	1.65	12.60	4.81	4.05	7.94	10.14	14.20	1.74	2.12
Minimal JE of Residuals (Maximal Mutual Information)	66.27	33.39	-	0.34	-	-	-	-	-	-	-	-
Mean Compromise Weights	60.04	16.22	2.57	1.04	4.47	1.80	1.50	2.76	3.46	4.79	0.62	0.72

Table 4. Optimal Span Values for Each Rotated Criteria (Bootstrap averages)*.

.1	2	3	4	5	6	7	8	9	10	11	12
0.756	0.708	0.787	0.79	0.788	0.849	0.812	0.83	0.811	0.804	0.814	0.849

* polynomial fit of order 1 was the best for each case.

Fig. 4 depicts the overall financial performance of BRICS healthcare companies, as proxied by the weighted sum of partial utility functions, under different weighting schemes. Utility function computed based on mean compromise weights (cf. Table 3) entered as the dependent variable in a neural network regression, where business environment variables (cf. Table 1) served as explanatory variables. As regards the neural network architecture, Fig. 5 reports on the 10-fold cross-validation results for the optimal single-layer structure. As one may see, five neurons and a decay rate of 0.01 yielded a minimal RMSE value of 0.906. Olden et al. (2002) suggested analytical steps for performing sensitivity analysis under a given neural network architecture. Its results, in terms of the relative importance of each business environment variable, are reproduced in Fig. 6. It is noteworthy the role of business freedom, government integrity, and the company´s Tobin-q indicator in achieving higher financial performance in the healthcare sector. On the other hand, tax burden, monetary freedom, and government spending may interfere negatively.

Business freedom is an indicator of the efficiency of government regulation of business, it mainly reflects the level of difficulty for a business to start, operate and close during the production process, a higher degree of business freedom increases the flexibility of a business to operate in the industry, the company will freely enter or exit into the industry based on the market forces, this is supposed to improve the optimal allocation of resources and the companies could be able to use their comparative advantage to improve their financial performance.

According to heritage.org, government integrity is related to freedom of corruption, a higher level of government integrity indicates that there is a lower level of corruption. The level of corruption can be measured by the commonly used corruption perception index provided by Transparency International, and the value of which ranges from 0 to 10 with a higher value indicating a lower level of corruption. A higher level of government integrity (a lower level of corruption) obviously will reduce the cost of production for all the economic entities across different economic sectors including the healthcare industry, the companies would be able to save the cost of bribing the government or industry officials and use the funds instead in the production process or other production activities such as research and innovation, this cost-saving is supposed to promote financial performance.

Tobin Q is an indicator of the power of Monopoly. Lindenberg and Ross (1981) argue that companies operating in a competitive environment would have a value of Tobin q near to 1, while the companies will have a certain level of monopoly power or would be able to have a production cost lower than the industry average when the value of Tobin Q is higher than 1. From our results, we argue that a higher level of Tobin Q increases the competitive power of the companies, they will be able to not only save the cost but also have a level of market power in setting the price level, this is supposed to improve the level of financial performance.

The tax burden is a measure related to the amount of tax imposed by the government, a higher level of the tax burden will increase the operating cost for the companies and will hurt financial performance. This is in line with Zhang et al. (2014) who find that there is a negative influence of tax burden on financial performance for the manufacturing industry in China. The monetary freedom is an indicator of price stability with an assessment of price controls, as defined by the heritage foundation. The price stability is mainly reflected from the level of inflation is the most important component in this indicator, followed by the degree of price control from the government. A higher level of inflation leads to a higher level of cost, which deteriorates the company's financial performance (Mahtani and Garg, 2018). Finally, regarding the impact of government spending on financial performance, Nekarda and Ramey (2011) argue that an increase in government demand raises outputs but will lower the product wages and labour productivity, while a decrease in the level of labour productivity can be regarded similar as the increase in the operational cost which further exerts a negative influence on company financial performance.

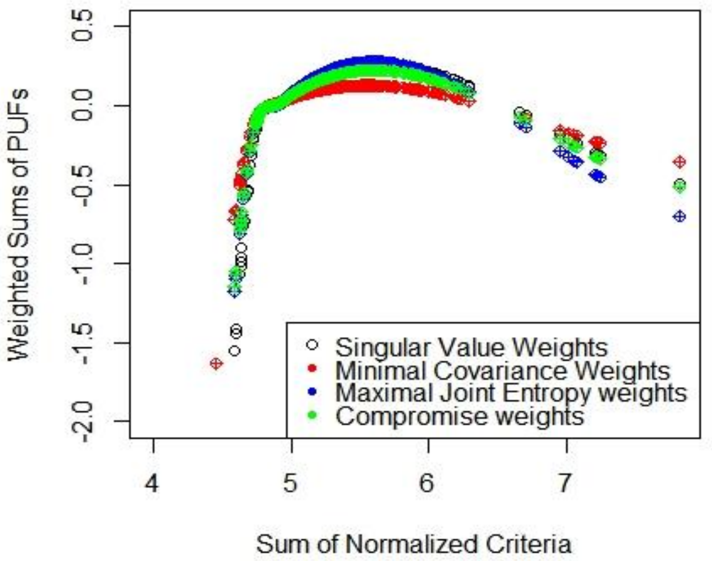

Fig. 4. Overall financial performance (as proxied by utility functions) under different weighting assumptions.

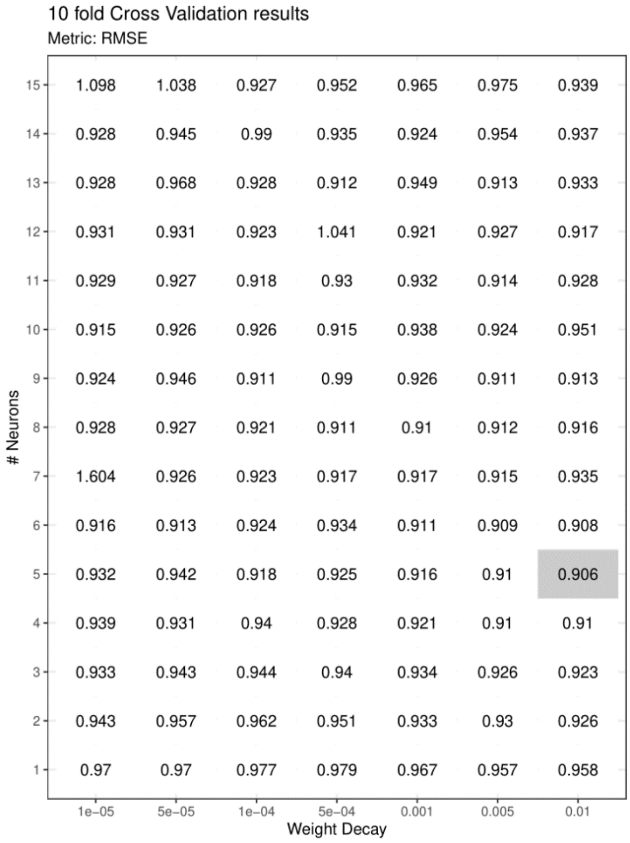

Fig. 5. 10-fold cross-validation results

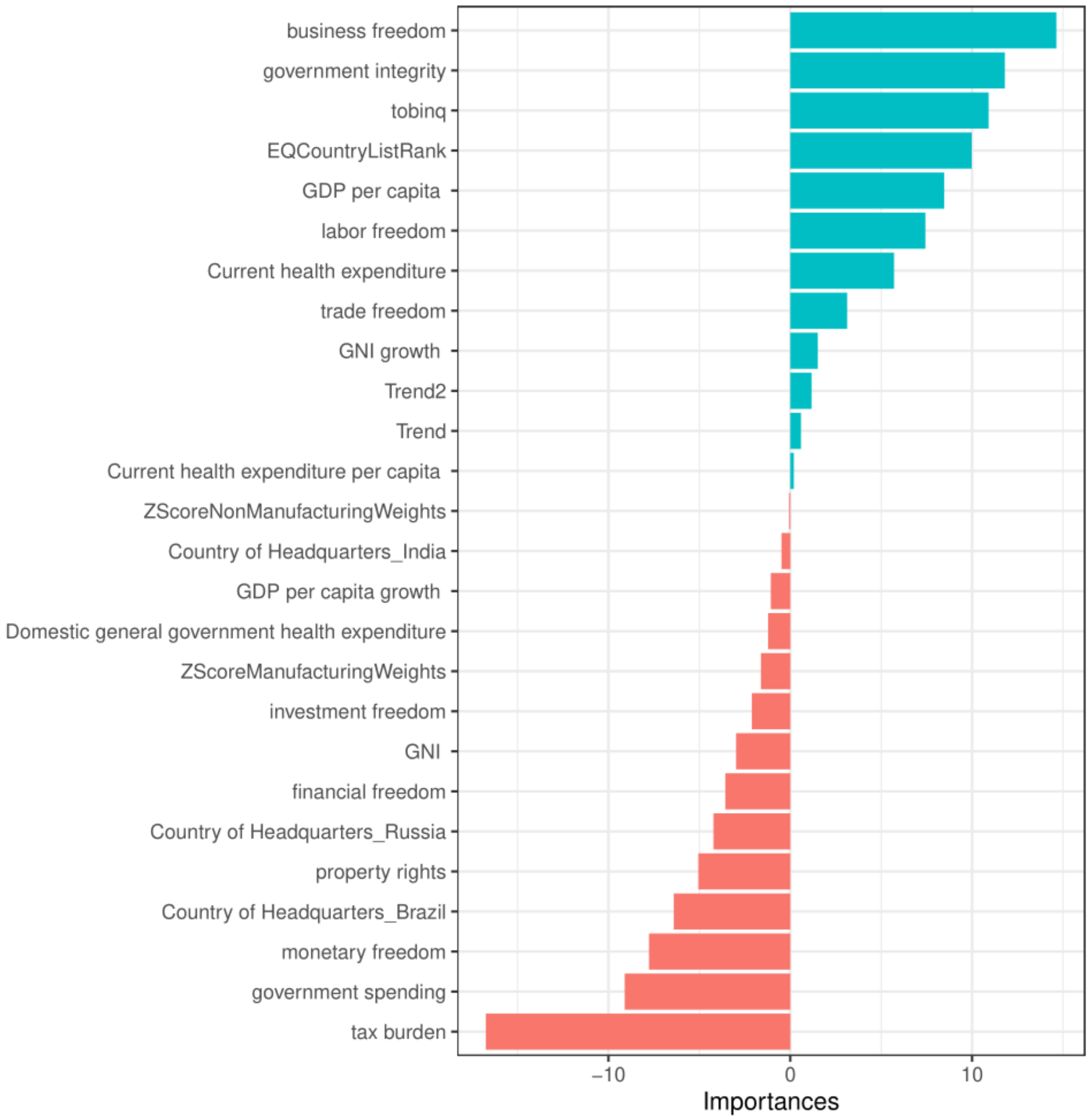

Fig. 6. Olden et al. (2002) sensitivity analysis on relative importance of business environment variables.

6. Conclusions

The financial performance of healthcare companies is an important research topic, in particular for the developing countries like BRICS considering that the fact that these countries engaged in large volumes of economic activities for higher economic growth. This results in a deterioration in the condition of the natural environment and further negatively influence people's health. Increasing the accessibility of the citizens to get access to the products and services provided by the healthcare industry at a reasonable price would be one of the priorities for the government. In addition to relevant government policies to facilitate the achievement of this, the healthcare companies themselves play an important role in achieving this goal by improving their financial performance.

The literature studies over the past two decades have made some attempts and efforts in estimating the financial performance of healthcare companies or hospitals using three different groups of methods including the accounting ratios, the non-parametric data envelopment analysis as well as the balanced scorecard approach. The current study differentiates itself from the previous research and contributes to the literature in a significant manner by proposing a novel approach to estimate an overall financial performance index based on weighted additive utility functions given a set of financial performance criteria. indicate that the values of financial performance range between 0.7 and 0.85, indicating that the financial performance of the BRICS healthcare companies is not low although there is still room for further improvement. We further find that both the company-specific factors including current assets, level of debt and liability, the company's Tobin Q are significantly related to the financial performance. In addition, various macroeconomic indicators such as business freedom, government integrity, tax burden, monetary freedom as well as government spending are the determinants of the financial performance of healthcare companies in BRICS.

Our study provides important policy implications for financial performance improvement of healthcare companies in BRICS: 1) increase the size of the operation would be helpful to improve the financial performance, this is supposed to reduce the cost and increase the competitive power; 2) reduce the amount of debt/liabilities and introduce or increase the use of equity finance; 3) from the government level, it is recommended that a free market environment would be helpful for performance improvement, other macroeconomic policies can be considered by the government include reducing the tax burden and the level of inflation rate; 4) a more transparent and accountable government with a lower level of corruption with actually benefit the healthcare industry; 5) the government would also consider the reduce the amount of spending.

The main limitation of the current study lies to the fact that although innovative weighted additive utility functions are proposed to derive the performance index, no alternative parametric or non-parametric method is used, which makes the findings of the current study less robust. Also, the current study does not point out the financial performance of the healthcare companies on a country basis and no information is provided regarding the financial performance of health companies in each country on an annual basis. Therefore, further efforts should be made to address the above issues.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix. Significant criteria correlation pairs (legends to Fig. 1 – right).

Code	Significant Correlation Pair	Sign
[1]	"TotalCurrentAssets TotalAssetsReported"	(+)
[2]	"TotalCurrentAssets RetainedEarnings"	(+)
[3]	"TotalCurrentAssets TotalEquity"	(+)
[4]	"TotalCurrentAssets NetIncomeAfterTaxes"	(+)
[5]	"TotalCurrentAssets BasicNormalizedEps"	(+)
[6]	"TotalCurrentAssets CashFromOperatingAct"	(+)
[7]	"TotalCurrentAssets CashFromInvestingAct"	(+)
[8]	"TotalCurrentAssets CashFromFinancingAct"	(+)
[9]	"TotalCurrentAssets FreeCashFlow"	(+)
[10]	"TotalCurrentAssets TotalDebt"	(+)
[41]	"NetIncomeAfterTaxes CashFromInvestingAct"	(+)
[53]	"CashFromOperatingAct CashFromFinancingAct"	(+)
[63]	"CashFromFinancingAct TotalLiabilities"	(+)
[66]	"TotalDebt TotalLiabilities"	(+)
[23]	"RetainedEarnings NetIncomeAfterTaxes"	(-)
[25]	"RetainedEarnings CashFromOperatingAct"	(-)
[36]	"TotalEquity FreeCashFlow"	(-)
[56]	"CashFromOperatingAct TotalLiabilities"	(-)
[57]	"CashFromInvestingAct CashFromFinancingAct"	(-)
[58]	"CashFromInvestingAct FreeCashFlow"	(-)
[59]	"CashFromInvestingAct TotalDebt"	(-)
[60]	"CashFromInvestingAct TotalLiabilities"	(-)
[46]	"BasicNormalizedEps CashFromOperatingAct"	(-)
[47]	"BasicNormalizedEps CashFromInvestingAct"	(-)
[48]	"BasicNormalizedEps CashFromFinancingAct"	(-)
[49]	"BasicNormalizedEps FreeCashFlow"	(-)
[50]	"BasicNormalizedEps TotalDebt"	(-)