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Research article

A multi-criteria decision-making approach to rank the sectoral stock indices of national stock exchange of India based on their performances

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Abstract: The ideal sector for an investment is a challenge for any capital market investor. This complexity is primarily attributed to the dynamic and volatile nature of public policies and macroeconomic factors that indirectly impact a sector's growth. In recent years, India in particular, has witnessed dynamic policies being implemented by the Government, such as Demonetization and Goods and Services Tax (GST), which led to sudden changes in the market forces. Thus, it is imperative that researchers focus on developing new scientific techniques for selecting the ideal sector to invest in capital markets. Understanding and analyzing a sector's behaviour is of prime importance to investors in any emerging capital market. This task appears to be complex as an investor needs to decide from a diverse set of sectors, where performance ranking can conflict with another for different variables. A volatile sector might be ranked higher on pure returns but would be ranked lower if risk-adjusted performance was considered. This is commonly referred to as a multiple criteria decision-making (MCDM) problem. In this paper, we consider the data of eleven Nifty sectoral indices from the National Stock Exchange (NSE) of India from January 2017 to December 2018. We apply three MCDM methods—COPRAS, SAW, and TOPSIS to rank the sectors and provide a holistic overview of their performance. Additionally, we propose a hybrid-ranking approach to solve the issue of divergent rankings from different MCDM techniques. We conclude that Nifty Financial service is the best performer in this volatile period. Once the rankings were obtained, we confirmed our results with actual fundamental events that took place in the economy. Through our research, potential investors can utilize our technique to rank the performance of sectoral indices for their specific region at any given time period.

Keywords: Indian stock market; multiple criteria decision-making (MCDM); TOPSIS; SAW; COPRAS; spearman's rank correlation coefficient; GST; demonetization

JEL Codes: C02, C61, G11

1. Introduction

The Indian capital market is the seventh-largest financial market, having a significant share in the world economy (Modak, 2018). Over recent years, the country's economic development has experienced accelerated growth. This growth had an enormous impact on the Indian capital market, attracting various foreign investors to invest in the Indian Market. On November 8 2016, the Indian Government announced the demonetization of all ₹500 and ₹1,000 banknotes. Subsequently, on July 1, 2017, the Indian Government announced a tax on the supply of goods and services (GST) to introduce a single taxation system for streamlining various indirect taxes. Thus, there were two significant events in a short period, taking the economy in a new direction. Towards the end of 2018, India had a market capitalization of $2.1 trillion (Modak, 2018). Since 2018 the market grew by over 6% during the following year (Vijayakumar, 2019). The accessibility to the Indian markets to investors has improved with the development and progress of information technology and policies in the country. It is an unstated assumption that each investment is associated with risk factors based on market forces and financial indicators, especially due to the volatile nature of the stock market. However, the optimum investment is not only based on a single security, but the weighted average of various securities for the same sector referred to in the Indian stock market as National Stock Exchange Fifty or as Nifty 50. A stock market index primarily represents a sector or an industry. The Nifty 50 index constitutes 50 companies in 13 industries in the Indian economy and is based on a free-float market capitalization-weighted index. The valuation and movements within these indices depend on company performance, government policies, crude oil prices, climate changes, political factors, and several others.

The motivation behind this paper is to analyze and rank the relative performances of various sectors associated with the National Exchange of India (NSE) during this period of unprecedented economic transformation. This ranking, in turn, can guide an investor to understand the right sectors to invest. In this paper, we develop a hybrid-ranking technique to perform a relative ranking of the sectoral indices of NSE to determine the best-performing sector for investments. We use multiple criteria decision-making (MCDM) approaches and Spearman's rank correlation coefficients techniques. Additionally, we also find the top and worst-performing indices during this crucial period and analyze the best possible MCDM methodologies to rank indices in the stock market. Portfolio managers are interested in getting high returns for their investors, but stocks that essentially bring high returns also carry a high risk of losing money. Additionally, investor preferences, manager constraints, and many other parameters can produce divergent results for ideal investments.

The decision-making process involving predicting and estimating the risk of multiple conflicting criteria can be viewed as a multiple criteria decision-making (MCDM) problem. MCDM is based on solving and planning decisions when several conflicting criteria are involved. MCDM doesn't derive the unique best solution for a given sector; it, however, strengthens and improves the quality of the decision-making process by allowing the decision-maker to differentiate between the distinctive solutions (Hwang and Lin, 1987; Hota et al., 2018a). The MCDM approaches, using mathematical and optimization techniques, provide appropriate rankings. The Multi-Criteria Decision Analysis (MCDA) is extensively used in all industries due to its versatile scope for enhancing the quality of decision-making, such as the sugar industry (Anojkumar et al., 2014), the aviation industry (Gudiel Pineda et al., 2018), and for several applications in the finance industry (Marqués et al., 2020). Through this study, we have effectively employed this technique in the Indian stock market to rank the indices and identify the optimal sectors for investment purposes.

This paper presents rankings of the different indices of the Indian stock market through the MCDM approach. The three MCDM methods—COPRAS, SAW, and TOPSIS methods combined with Spearman's rank correlation coefficient are employed to make suitable decisions while investing in the Indian Stock Market. The paper's primary objective is to potentially help investors study the market and industry performance through a look-back analysis of the movements observed in the Indian Stock Market during the two-year time frame of January 2017 to December 2018. Hence through these trends and rankings observed in this paper, investors can make a more informed decision, examine prior mistakes, and find potential solutions regarding industries suitable for their investment. For our analysis, we use the National Stock Exchange (NSE) of India. To the best of our knowledge, this paper is the first attempt to utilize MCDM methods as a precise and reliable technique to rank sectors for suitable investment decisions in the NSE. Furthermore, the accuracy of the obtained results is confirmed by analyzing them with the market factors that affected certain indices during the given period. Though our paper uses a similar approach described by Hota et al. (2018b), our indices selection, data collections, and interpretations are different. Unlike Hota et al. (2018b), our paper selects indices based on industry sectors and analyzes the cumulative performance after two years. To justify our contributions, we provide a comparison between our study and the other related existing studies (see Table 1).

In Summary, this paper makes the following contributions as indicated in Table 1:

- We propose the MCDM models to rank the performance of sectors in the Indian Stock Market. Investors can use the same model framework to rank the sectoral indices for their specific region.
- We evaluate the performance of sectoral indices during the volatile economic period from 2017 to 2018.
- We provide empirical evidence through actual fundamental events that support the theoretical ranking with the MCDM models.
- We rank the sectors based on their performances and recommend the best performing sector to invest in the Indian Stock Market along with valid reasoning for its selection.

The rest of the paper is organized as follows. Section 2 contains the literature review, followed by Section 3, consisting of an index selection framework and the procedures used for the MCDM methodologies: COPRAS, SAW, and TOPSIS. The data used and results obtained from these three methods are illustrated in Section 4, and the conclusions are summarized in Section 5.

Table 1. A comparison of our study with some related existing studies.

Studies	Indian Stock Market?	MCDM Model?	Multi-criteria Performance?	Hybrid-Ranking	Demonetisation & GST Period
Isa et al. (2020)	No (Malaysian stock market)	No (Co-Integration Test)	No (cointegration)	No	No
Lakshmi (2013)	Yes (Nifty Indices)	No (ARCH Model)	No (Volatility)	No	No
Guha et al. (2016)	Yes (Nifty Indices)	No (Factor Analysis)	No (Risk)	No	No
Trabelsi (2020)	Yes (BSE Indices)	No (Granger Causality test)	No (Gold returns)	No	No
Srivastava (2020)	Yes (Nifty Indices)	No (Regression Model)	No (Correlation)	No	No
Tripathi (2014)	Yes (Nifty Indices)	No (Regression Model)	Yes	No	No
Kumar and Singh (2020)	Yes (Nifty Indices)	No (Unit Root Test)	No (Causal relationship)	Yes	No
Agrawal and Sangeetha (2019)	Yes (Nifty Indices)	No (Event Study Methodology and Granger Causality test)	Yes	No	Yes (Demonetisation)
Hota et al. (2018b)	Yes (BSE Indices)	Yes	Yes	No	No
Poklepović and Babić (2014)	No (Croatian Stock Market)	Yes	Yes	Yes	No
This study	Yes (Nifty Indices)	Yes	Yes	Yes	Yes

2. Literature survey

There are several studies available in the existing literature that have looked into the fundamental constituents influencing the stock markets by understanding investors' sentiments. Let us examine the earlier studies performed by various researchers to analyze sectors and study trends for movements in the market for the right investments in Indian and other world economies during different fiscal years. Lakshmi (2013) uses the ARCH (Autoregressive Conditional Heteroskedasticity) model to measure the volatility in Nifty of various sectoral indices in India during the highly volatile period of 2008. The results show that the sectors having the highest and lowest volatilities are the Realty sector (83%) and the Banking sector (12%), respectively. She records Nifty's volatility as 23%. Shanmugasundram and John (2013) studies the risk factors across the sectoral indices and investigates if there is any risk relationship at various time intervals from

2004 to 2012. They use the two-sample T-test and One-way ANOVA between subjects to identify the risk factor difference across the risk of sectoral indices and CNXNifty index. Although the results indicate no difference in the Standard deviation of multiple sectoral indices, there is a significant change in the mean scores of various time intervals. In a study, Rajamohan and Muthukamu (2014) use the Pearsons correlation coefficient technique to understand the extent of influence of the banking sector on the performance of all the other Nifty indices by analyzing the market during the global recession of 2008. The results state that the Bank Nifty index has a positive influence on all almost all the sectoral indices of NSE in both bull and bear phase market movements.

Poklepović and Babić (2014) use a hybrid MCDM approach for selecting the right stocks in the Croatian capital market. Their results propose a model that provides a final ranking of the listed stocks by resolving the divergent rankings from different MCDM approaches with a hybrid technique. It may be noted that their study is on stocks, not on sectors. Tripathi et al. (2014) evaluate the impact of various global factors and the degree to which these global factors affected the selected five Indian sectoral indices (Auto, Bank, Energy, FMCG, and IT) at NSE for the given period 2005–2013. Five different macroeconomic variables such as Crude oil price, Dollar value (INR/USD), Foreign Institutional Investment, Foreign Exchange Reserves, and Current Account Balance have been considered as independent variables to study the impact of global factors. They use regression and correlation techniques to conclude the significant relation these variables have on each index individually, stating that Foreign Institutional Investment is the most significant macroeconomic indicator affecting all sectoral indices in India. Ramkumar et al. (2015) study the efficiency of two major stock exchanges in India, namely BSE and NSE sectoral indices, by using daily share price returns for fiscal years 2009–2014. It is tested by the random distribution and weak-form efficiency in BSE and NSE sectoral indices to help investors make more suitable investment decisions. He examines the returns of these indices through descriptive statistics and confirms that BSE IT index and NSE IT index performed the best during the sample period. Joshi and Giri (2015) analyze the impact of a predetermined set of macroeconomic factors and sectoral GDP on different sectors of BSE from 2003:Q4 to 2014:Q4. They employ the Auto Regressive Distributed Lag (ARDL) approach to examine the cointegration and long-run stability between the sectoral BSE indices with the sectoral contribution in GDP along with other controlled variables. Furthermore, they use VECM based Granger causality and Variance Decomposition (VDC) techniques. The results from all three techniques show the significant co-integrating of the relationship between sectoral GDP and sectoral stock indices in India.

Guha et al. (2016) study the risk in terms of Beta in all sectoral indices of NSE and rank them accordingly in terms of return per unit of risk. They also use factor analysis among eleven sectoral indices. The factor analysis shows that the sectors having higher sensitivity are Realty, Metal, and IT, whereas sectors that are defensive are FMCG, Pharma, and Auto. It also suggests that FMCG, Pharma, and Auto are the sectors where investors should take keen interest since these results are encouraging in terms of volatility (being defensive) and score higher return per risk. Sangeetha and Makhariya (2017) focus on the dependence of Nifty on its sectoral variants and the movements caused by these sectors during a seven-year time frame. The methodologies applied are the cointegration test, casualty test, unit root test, and correlation analysis on the index data. The results reveal that Auto, Public Sector Undertaking (PSU) banks, and Private banks are the sectors that have a uni-directional relationship with Nifty, suggesting that the markets are highly dependent on the performance of these sectors. On the other hand, there exists a unilateral relationship between Nifty and Media, i.e., Nifty causing movement in media, this is a result of increased spending in media and entertainment when the overall markets are outperforming. The realty sector is one more sector where Nifty causes movement. Manimaran and Vijai Anand (2017) evaluate the return, risk, and volatility of the BSE sectoral indices for the period from Jan 2007 to December 2016. The primary objective of the paper is to classify sectors as High, Medium, and Low, based on the metrics of return, sensitivity, risk, and volatility. The results highlight that FMCG, Healthcare, Banks, and the Auto sectors yielded high returns; manufacturing-based industry yielded moderate returns, whereas Technology and PSU had an underwhelming performance during the designated period. A recent study by Hota et al. (2018a) uses AHP, AHP-TOPSIS, and AHP-SAW methods to rank six stock indices of the Bombay Stock Exchange (BSE) of India based on 2011–2014 data. From the set of proposed models, their empirical results showed that the integrated approach of AHP-GP produced a greater annual return of 35.15% against the expected 40% annual return with the lowest risk value.

Attri and Gupta (2019) investigate the presence of long-term memory with reference to structural changes/breaks in the Indian Stock Market. They use the Hurst Exponent in Rescaled Range Analysis and the Multiple Break Test on the daily returns of sectoral indices from January 2010 to May 2018. The paper attempts to pursue whether the long memory effect is contingent upon structural breaks. Their analysis concludes that all sectoral indices show the long memory effect except the Nifty Private Bank. Pathak and Patel (2019) study the impact of demonetization on the Indian Stock market. This research used Event Study Methodology and Granger Causality test to analyze the impact of various sectors (Nifty Bank, Nifty Pharma, Nifty FMCG, and Nifty Realty) on the Nifty50 index during the Demonetisation Period. The time period selected included both pre and post-event windows from 1/4/2016 to 7/11/2016 and 8/11/2016 to 31/3/2016. The result shows that Nifty50 was highly dependent on the performance of the Realty sector while all the other pairs have neither a uni-directional nor a bi-directional relationship. However, when the results were analyzed Post Demonetisation, it showed that Nifty50 was highly dependent on the performance of the Banking Sector. In contrast, all the other pairs had neither a uni-directional nor a bi-directional relationship. Gupta et al. (2021) rank the performance of Indian private sector banks based on their financial capability. Their study focuses on those banks that are listed in the Bombay Stock Exchange (BSE), for the period from 2014–2015 to 2018–2019. In their paper, IV-TOPSIS is used to evaluate the cumulative performance (combined performance of 5 years) of banks. Additionally, the study performs a sensitivity analysis to check the robustness of the method. The results show that the HDFC bank is the top performer and is ranked first for all the years consecutively during the period 2014–2019 and has set a financial indicator benchmark for the other competitor banks.

Trabelsi et al. (2021) investigate the relationship between the returns of gold and seven sectoral indices in the Bombay Stock Exchange (BSE) for the period from January 2000 to May 2018. This paper applied the Granger causality test and studied the dependence based on different frequency and quantile levels. The results of the paper indicate the changes in gold prices are significantly independent of the returns of the BSE sectoral indices, and moreover, gold can predict the future returns of the Consumer Durables, Oil & Gas, and the FMCG stock indices, helping investors predict and react to where the market is headed. Srivastava (2020) examines the theoretical and empirical relationship between ten sectoral indices on NSE. The price movements for six years from January 2012 to April 2018 weekly. The correlation study and regression model are implemented to derive the relationship between the indices. The relationships between all indices are categorized into three parameters—Weak Correlation, Moderate Correlation, and Strong Correlation. MD ISA and Mohamad Azwan et al. (2020) study the cointegration and causality in the Malaysian stock market among the FBM Hijrah Shariah index (HSI), Mid70 index (Mid70), and seven sectoral indices from Jan 2009 to Dec 2018. Their cointegration test shows co-movements and long-run (LR) equilibrium among the HSI, Mid70, and sectoral indices. Kumar and Singh (2020) analyze the trend, pattern, and causal relationship of the Nifty-Fifty and sectoral indices. They have employed the unit root test and Granger-causality test for their analysis. The findings indicate that the financial services sector performed better, followed by the banking sector amongst all the indices.

Poklepović and Babić (2014) consider individual stocks from the Croatian stock market. But our study considers indices and not stocks. The financial health and characteristics of stock markets differ from one to another. We focus on the analysis of industries rather than individual high valued or low valued stocks in the Indian capital market, as the main objective is to provide a holistic overview. Industries refer to a group of companies operating in the same business sphere; hence there are multiple stocks in one index. Each stock has its weightage in its index depending on company size, performance, and other relevant factors. There is a sectoral distribution in the index. The risk due to certain factors such as a senior management resignation/death specific to a certain stock/company can be mitigated significantly with index investments.

3. Indices and methods

In this section, the authors explain the index selection frameworks, a brief description of methodologies used for the analysis, including AHP, COPRAS, SAW TOPSIS.

3.1. Index selection framework

Data for this study is obtained from the National Stock Exchange (NSE) database, and it includes information on Nifty's sectoral indices returns and trading volumes in the period from January 2017 to December 2018, averaged over the sample period for 11 indices which are constituents of stocks within the Indian capital market. The number of trading days observed is 494. It also includes the most important fundamental and stock market indicators for the selected index in that period.

3.2. Methods

The below image provides a step-by-step analysis of how the research was conducted. Each technique is further elucidated sequentially in the latter part of the paper.

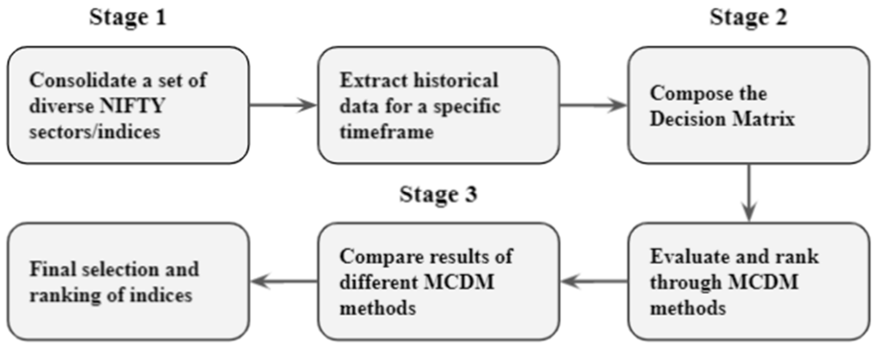

Figure 1. Flowchart of Methods and its stages.

3.2.1. The analytic hierarchy process (AHP)

Analytic hierarchy process (AHP) is a powerful analytical tool developed by Thomas L. Saaty to solve multi-attribute decision-making problems in multiple unstructured conflicting situations (Saaty, 1980). The primary emphasis of this structured technique is a comparison of a pair of quantities by deriving numeric measurements from subjective and preferential opinions of the decision-makers.

The AHP approach is divided into a four-step process (Vachnadze and Markozashvili, 1987; Podvezko, 2009; Veisi et al., 2016). These steps are:

(1) The decision-maker deconstructs the problem and identifies the major components and common characteristics of the problem. Then, it develops a hierarchy having multiple levels based on the common characteristic of elements at a particular level. The topmost level has the highest priority, followed by the lower levels and, finally, the lowest level of possible alternatives. The decision-maker develops this model based on his/her preferences and requirements for the problem.

(2) Furthermore, pairwise comparisons are made at different levels to build a judgment matrix. The judgment matrix is created using a 1-9 scale (1 having the least preferred and 9 having a maximum preference). The pairwise comparisons help in simplifying the decision-making process.

(3) Following the pairwise comparisons, the consistencies are measured, and the priority of the elements in the levels is established, the priorities are synthesized, and weight-coefficients for each element are determined.

(4) The sum of weight elements on each hierarchy level is equal to 1 and allows the decision-maker to rank all hierarchy elements in terms of importance.

3.2.2. Complex proportional assessment method (COPRAS)

The complex proportional assessment method (COPRAS) approach is another MCDM tool developed in 1994 (Zavadskas et al., 1994). This technique takes into account the influence of direct and proportional dependencies of significance and utility of considered alternatives in the scenario of multiple conflicting criteria. The selection of the best alternative is based on considering both the ideal and anti-ideal solutions. The degree of utility is determined by comparing the considered alternatives with the most optimal one. The steps of COPRAS's methodology are as follows (Popović et al., 2012; Xia et al., 2014):

(1) Develop the decision matrix

$$X = \left[x_{ij}\right]_{m\times n} \tag{1}$$

where x_{ij} is the evaluation of the i^{th} alternative on the j^{th} criteria, m is the number of alternatives, and n is the number of criteria, respectively.

(2) The normalization of the decision matrix using the following equation:

$$R = \left[r_{ij}\right]_{m\times n} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

(3) Determination of the weighted normalized decision matrix, D, by using the following equation:

$$D = \left[y_{ij}\right]_{m\times n} = r_{ij}.w_j,\ i = 1,2,\dots,m;\ j = 1,2,\dots\dots,n \tag{3}$$

where r_{ij} is the normalized evaluation value of i^{th} alternative on j^{th} criterion, and w_j is the weight of j^{th} criterion, respectively.

The sum of weighted normalized values of each criterion is always equal to the weight for that criterion:

$$\sum_{i=1}^{m} y_{ij} = w_j,\ j = 1,2,\dots,n \tag{4}$$

(4) The sums of weighted normalized values are calculated for both the beneficial and non-beneficial criteria:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij},\ \ S_{-i} = \sum_{j=1}^{n} y_{-ij}\ ,\ i = 1,2,\dots,m \tag{5}$$

where the higher the value of S_{+i}, the better the alternative, and the smaller the value of S_{-i}, the better the alternative. The values y_{+ij} and y_{-ij} are the weighted normalized values for the beneficial and non-beneficial criteria, respectively.

(5) We determine the relative significances of the alternatives, Qi. The higher the value of Qi, the greater the priority of the alternative. The relative preference value (priority), Qi of the ith alternative is defined by

$$Q_i = S_{+i} + \frac{S_{-min}\cdot\sum_{i=1}^{m} S_{-i}}{S_{-i}\cdot\sum_{i=1}^{m}\left(\frac{S_{-min}}{S_{-i}}\right)},\ i = 1,2,\dots,m \tag{6}$$

where S_{-min} is the minimum value of S_{-i}.

(6) Finally, we calculate the quantitative utility, Ui, for ith alternative. The degree of an alternative's utility is linked to its relative preference value (Qi) and estimated by comparing the priorities of all alternatives with the most efficient.

$$U_i = \frac{Q_i}{Q_{max}}.100\% \tag{7}$$

In the above, Q_{max} is the maximum relative preference value.

3.2.3. Simple additive weighting (SAW) Technique

This method is also known as the weighted linear combination or scoring method. It is one of the most sought after approaches in the multiple criteria decision-making field. In this approach, to each performance metric, an important weight is assigned, obtained either directly from field experts or from different analytical methods for the importance of weight assessment. The total score of each performance metric is calculated by multiplying the scaled value given to the alternative of that attribute with the weights of relative importance directly assigned by the expert. The SAW method utilizes a matrix normalization process through a proportional linear transformation of the raw data. These products are summed up for all the attributes, and the final rating of each alternative is obtained. After the total scores are computed for each alternative, the alternative with the highest score (the highest weighted average) is the one given to the decision-maker (Siahaan et al., 2017; Gupta et al., 2017; Tahyudin et al., 2018).

3.2.4. Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS is a multi-criteria decision analysis method, originally developed by Hwang and Yoon (1981). This approach is based on the principle that the proposed alternative would have the closest Euclidean distance to the ideal point and the longest distance to the negative-ideal point. TOPSIS considers the distances to both the ideal and the negative-ideal solutions simultaneously by taking relative closeness to the ideal solution. Hence, by this method, the final rankings have been determined (Tahyudin et al., 2018).

The methodology is as follows:

(1) Normalization of the decision matrix as given below:

$$D = \left[x_{ij}\right]_{m\times n} \tag{8}$$

where x_{ij} is the performance of the i^{th} alternative on the j^{th} criterion, m is the number of alternatives, and n is the number of criteria.

(2) Determining the ideal and negative ideal solution:

The ideal solution has the best values for each attribute:

$$A^{+} = \left\{\left(\max x_{ij} \mid j \in J\right).\left(\min x_{ij} \in J'\right),\ \ i = 1, 2, \dots, m\right\} = \{x_1^{+}, x_2^{+}, \dots, x_n^{+}\} \tag{9}$$

where J is a set of benefit attribute indices, and J' is a set of cost attribute indices.

The negative ideal solution:

$$A^{-} = \left\{\left(\min x_{ij} \mid j \in J\right).\left(\max x_{ij} \in J'\right),\ \ i = 1, 2, \dots, m\right\} = \{x_1^{-}, x_2^{-}, \dots, x_n^{-}\} \tag{10}$$

Therefore, it can be inferred that these alternatives inside the offered set of alternatives will not exist.

(3) Transformation of attributes:

This step is crucial to obtain non-dimensional values, which allow the comparison of attributes. One way of transformation is vector normalization, which divides every column of the decision matrix (vector X_j) by the norm of that vector. Column vectors in the decision matrix then become:

$$\bar{X}_j = \frac{X_j}{\|X_j\|} = \frac{X_j}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \ j = 1, \ 2, \dots, n. \tag{11}$$

(4) Measuring the distance:

$$W = \{w_1, w_2, \dots, w_n\} \tag{12}$$

Assuming the weights by the decision maker, then the distance of any alternative A_i from A^+ and A^- as a weighted Euclidean distance as:

$$S_{i+} = \sqrt{\sum_{j=1}^{n} \left[\frac{w_j\left(x_{ij} - x_j^+\right)}{\|X_j\|}\right]^2} \tag{13}$$

$$S_{i-} = \sqrt{\sum_{j=1}^{n} \left[\frac{w_j\left(x_{ij} - x_j^-\right)}{\|X_j\|}\right]^2} \tag{14}$$

(5) Calculating relative closeness (*RC*) to the ideal solution:
The relative closeness of alternative A_i with respect to ideal solution A^+ is defined as:

$$RC_i = \frac{S_{i-}}{S_{i+} + S_{i-}} \tag{15}$$

Obviously, $RC_i = 1$ if $A_i = A^+$ and $RC_i = 0$ if $A_i = A^-$ An alternative is closer to the ideal solution as RC_i approaches to 1.

3.2.5. Spearman's rank correlation coefficient

Spearman's rank correlation coefficient determines the similarity amongst the resultant rankings of different MCDM methods. It calculates the correlation of rankings between the three methods of MCDM used in this report. Furthermore, the method that has the highest weighted average correlation when compared with the others is considered to be the most accurate method for decision-making (Gautheir, 2001). The normalized weight, estimated for each method, is employed to calculate the hybrid rank for each alternative.

Spearman's rank correlation coefficient between the k^{th} and the i^{th} MCDM method is calculated using the following equation:

$$\rho_{ki} = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n} \tag{16}$$

where n is the number of alternatives, and d_i is the difference between the ranks of the MCDM methods. Based on the value of ρ_{ki}, the average similarities between the k^{th} MCDM method and other MCDM methods can be calculated as:

$$\rho_k = \frac{1}{1-q}\sum_{i=1, i\neq k}^{q} p_{ki},\ k = 1,2, \ldots, q \tag{17}$$

where q is the number of MCDM methods. The larger the ρ_k value, the higher the value assigned to the MCDM method. The most preferred alternative (A^*) is given by:

$$A^* = \left\{ A_i \mid \max_i \left(\frac{\sum_{k=1}^{q} \rho_k r_{ik}}{\sum_{k=1}^{q} p_k} \right) \right\} \tag{18}$$

where r_{ik} is the outcome of the i^{th} alternative about the k^{th} MCDM method.

4. Data and results

In this section, the authors discuss the data collection process and evaluate the results from each of the MCDM approaches: COPRAS, SAW, and TOPSIS.

4.1. Data

In this paper, the eleven major Nifty indices from the Indian National Stock Exchange have been considered in the period from January 2017 to December 2018. The justification for selecting this specific period is to analyze the effects of two crucial unforeseen government policies: demonetization and GST on the Nifty Indices. The closing price at the end of each day and traded volumes are downloaded from the NSE database for each index (data source: https://www.nseindia.com/). Additionally, other indicators were obtained from the NSE database, such as standard deviation, mean, Beta, price-to-book ratio (P/B), price-to-earnings ratio (P/E), dividend yield (Div. Yield), trading volume, and average turnover (in crores).

Firstly, we obtain each index's daily return and then calculate the daily mean return and daily standard deviation. Average traded volumes are calculated from the daily volumes. Mean return is the average of the daily returns for each sector in the observed period. From this mean return, we estimate the standard deviation that measures the risk of a particular sector. Beta measures the volatility, or systematic risk, in comparison to the market as a whole. We have calculated Beta for each index with respect to Nifty 50. The price-to-earnings (P/E) ratio is used to compare a company's share price to the earnings per share. A high P/E ratio could mean that the stock is overvalued relative to its earnings, whereas a low P/E ratio can indicate that either the stock is undervalued or performing well relative to its past trends. The price-to-book (P/B) ratio is used to compare a firm's market to book value. Usually, a lower P/B ratio indicates an undervalued stock. However, it can also indicate a fundamental issue with the company. The dividend yield is the ratio of a company's annual dividend compared to its share price. A decline in the share price is usually offset by a rise in the dividend yield. Turnover in the stock market refers to the total value of the stocks traded during a specific period. It is a good indicator of the sector's overall health. A high turnover highlights a bullish investor sentiment, whereas a low turnover highlights a bearish investor sentiment. For P/E, P/B, dividend yield, and turnover, we have calculated the average of the daily values for the given time period. These criteria are industry-independent and represent the stock market indicators. Secondly, it is known that both financial statements and financial indicators can be different for financial and non-financial companies. Therefore, only the indicators suitable for calculation for both the financial and non-financial companies have been used. It should be noted that the selected indices belong to different industries, i.e., Energy, Infrastructure, Financial Services, Realty, Media, Pharma, Bank, and the IT sector. The initial data for this study is given in Table 2. It includes 11 indices, which have been formulated in such a manner that we achieve a decision matrix with multiple criteria. Eventually, each of these criteria will be given a certain amount of importance (weight) for better decision-making.

Table 2. Decision matrix.

Nifty Indices/ Parameters	Standard Deviation	Mean	P/E	P/B	Div. Yield	Volume	Beta	Turnover Avg.
BANK	0.872	0.087	35.623	2.916	0.445	129888879	1.062	3716.55
AUTO	1.009	0.003	35.522	5.961	0.722	42300792	1.128	2070.40
FIN. SERVICE	0.885	0.097	30.205	3.520	0.586	78557987	1.107	3808.66
FMCG	0.975	0.083	42.233	11.887	1.407	23819665	0.877	1263.44
IT	1.055	0.073	18.467	4.636	1.948	25948227	0.511	1722.44
MEDIA	1.151	0.003	41.043	6.057	0.548	20902485	0.964	401.45
PHARMA	1.281	−0.022	44.800	4.295	0.513	18314355	0.908	1363.32
REALTY	1.646	0.074	66.679	1.234	0.400	59318574	1.374	528.79
INFRA	0.935	0.034	43.715	2.177	1.258	182081826	1.056	2105.55
ENERGY	1.119	0.073	14.797	1.937	1.686	55903879	1.114	1974.67
MNC	0.842	0.075	29.563	6.087	1.468	35555872	0.965	1593.30

4.2. Results

From Table 2, it can be observed that the average traded volumes for each index in the decision matrix gives us an insight into an investor's sentiment for each sector. We have taken Nifty Bank as our reference to compare with the other sectors. The following are important insights from our analysis:

1. Investor behaviour towards indices with the same market price: For example, Nifty Bank and Nifty FMCG both were trading at similar price points (average share price) and had a similar growth during the period of our analysis, but volumes traded for Nifty Bank were much higher compared to Nifty FMCG. Higher volumes in comparison show that even though they belong to the same price point, investors were more positively inclined towards the bank sector rather than the FMCG sector.

2. Investor behaviour towards indices with a different market price: For example, Nifty Bank and Nifty Realty both were trading at vastly different price points during the period of our analysis. As per the law of demand, a product with a lower market price gives investors a greater amount of purchasing power. Investors could buy much larger volumes of low-priced Nifty Realty compared to the high-priced Nifty Bank. But as per actual data, people have traded Nifty Bank almost twice as compared to Nifty Realty. Therefore, this gives us a deep insight into investor's trading behaviour and proves the statement that investors are not at all market price-sensitive when we compare sectoral indices. They are more concerned about the growth and performance of the sector, and hence their inclination varies from time to time.

Using the AHP method, we developed a hierarchy for our performance metrics, with the highest priority to the daily mean return and the lowest priority to Beta, price-to-book ratio (P/B), and price-to-earnings ratio (P/E), respectively. The weights for further calculations are obtained using the AHP method and are given in Table 3.

Table 3. AHP results.

TOTAL	Standard Deviation	Mean	P/E	P/B	Dividend Yield	Volume	Beta	Turnover Avg.
1	0.105	0.316	0.053	0.053	0.211	0.105	0.053	0.105

An institutional investor is primarily concerned with their gross investment returns, and hence Mean has been given the greatest importance amongst all the parameters. Considering a two-year timeframe, we assume that the investor would prefer high dividend yields and turnover, low P/E and P/B ratio (undervalued indices), low Beta, and a low Standard deviation. As P/E and P/B ratios do not have a set desired criteria for an investor, hence they have lower importance when compared to the other parameters. The results obtained by COPRAS, SAW, and TOPSIS approaches are displayed in Tables 4, 5, 6, respectively.

Table 4. COPRAS results.

Nifty Indices	Sum of Beneficial Criteria	Sum of Non-Beneficial Criteria	S-(min.)/S_i	Q_i	U_i	Rank
BANK	0.087	0.019	0.925	0.112	100	1
AUTO	0.028	0.023	0.750	0.048	43.007	9
FIN. SERVICE	0.087	0.019	0.914	0.112	99.993	2
FMCG	0.072	0.029	0.607	0.088	79.152	7
IT	0.077	0.018	0.994	0.104	92.933	4
MEDIA	0.014	0.024	0.712	0.033	29.816	10
PHARMA	0.005	0.024	0.727	0.025	22.194	11
REALTY	0.054	0.029	0.611	0.071	63.185	8
INFRA	0.071	0.020	0.890	0.095	85.381	5
ENERGY	0.079	0.017	1.000	0.106	94.711	3
MNC	0.072	0.021	0.845	0.095	84.912	6

Table 5. SAW results.

Nifty Indices	Standard Deviation	Mean	P/E	P/B	Dividend Yield	Volume	Beta	Turnover Avg.	Sum	Rank
BANK	0.056	0.284	0.028	0.013	0.048	0.075	0.041	0.103	0.647	3
AUTO	0.065	0.010	0.028	0.026	0.078	0.024	0.043	0.057	0.332	9
FIN.SERVICE	0.057	0.316	0.024	0.016	0.063	0.045	0.042	0.105	0.668	1
FMCG	0.062	0.270	0.033	0.053	0.152	0.014	0.034	0.035	0.653	2
IT	0.067	0.236	0.015	0.021	0.211	0.015	0.020	0.048	0.631	5
MEDIA	0.074	0.008	0.032	0.027	0.059	0.012	0.037	0.011	0.260	10
PHARMA	0.082	−0.072	0.035	0.019	0.055	0.011	0.035	0.038	0.202	11
REALTY	0.105	0.239	0.053	0.005	0.043	0.034	0.053	0.015	0.547	8
INFRA	0.060	0.112	0.035	0.010	0.136	0.105	0.040	0.058	0.556	7
ENERGY	0.072	0.237	0.012	0.009	0.182	0.032	0.043	0.055	0.641	4
MNC	0.054	0.244	0.023	0.027	0.159	0.021	0.037	0.044	0.608	6

Table 6. TOPSIS results.

Nifty Indices	S+	S-	RC	Rank
BANK	0.067	0.173	0.719	2
AUTO	0.156	0.054	0.257	9
FIN.SERVICE	0.070	0.182	0.723	1
FMCG	0.085	0.158	0.651	6
IT	0.077	0.155	0.667	4
MEDIA	0.168	0.044	0.206	10
PHARMA	0.195	0.030	0.135	11
REALTY	0.104	0.141	0.577	7
INFRA	0.098	0.117	0.544	8
ENERGY	0.067	0.153	0.694	3
MNC	0.077	0.150	0.661	5

We obtain the ranks from each MCDM approach. It can be observed from Tables 4, 5 and 6 that there is an overlapping of rankings for the various indices. The tables provide weights for each criterion. The weights for further calculations are obtained using the AHP method. Based on the decision matrix and weights, the rankings for three MCDM methods are done. It can be concluded that the best indices to invest in are Nifty Bank, Nifty Energy, and Nifty Financial services, which have the lower ranks in all MCDM methods. The worse indices to invest in are Nifty Auto, Nifty Media, and Nifty Pharma, as they all have higher ranks in all MCDM methods.

Although the rankings from the different MCDM approaches have been obtained, we have utilized Spearman's rank correlation coefficient method to solve the problem of divergent rankings. In this way, we determine a unique hybrid rank for all the sectors and identify the best performing sector as our recommendation.

Table 7 below gives an overview of Spearman's rank correlation coefficients between rankings of the three MCDM methods. It was the starting point for the calculation of the weights and normalized weights provided in Table 8. It can be seen that the TOPSIS method was given the highest weight, indicating a good agreement between this method and other MCDM methods. SAW has the lowest weight, indicating a lower but still a good agreement between this method and other MCDM methods.

Table 7. Spearman's correlation coefficient.

Spearman Correlation coefficient	TOPSIS	SAW	COPRAS
TOPSIS	1	0.9	0.936
SAW	0.9	1	0.836
COPRAS	0.936	0.836	1

Table 8. Spearman's ranking.

Best Approach	TOPSIS	SAW	COPRAS
Weights	0.918	0.868	0.886
Normalized weights	0.344	0.325	0.332
Ranks	1	3	2

After obtaining normalized weights, as shown in Table 8, we incorporate a hybrid-MCDM ranking approach to obtain the optimal sector for investments. We calculate the weighted score using the ranking and normalized weights from each MCDM approach. The formulation is similar to the one which is used to calculate the expected portfolio return or volatility from a given set of assets:

$$\text{Weighted Score} = (NW_{TOPSIS} * Rank_{TOPSIS}) + (NW_{SAW} * Rank_{SAW}) + (NW_{COPRAS} * Rank_{COPRAS})$$

Here, "NW" represents Normalized Weight, and the "Rank" is the respective rank of the sector in each MCDM method. Table 9 displays the final ranking.

Hence, with the lowest weighted score, Nifty Financial Services has been considered as the optimal sector for investment purposes.

Table 9. Final ranking.

Nifty Indices	TOPSIS Rank	SAW Rank	COPRAS Rank	Weighted Score	Final Rank
BANK	2	3	1	1.993	2
AUTO	9	9	9	9	9
FIN.SERVICE	1	1	2	1.332	1
FMCG	6	2	7	5.032	5
IT	4	5	4	4.325	4
MEDIA	10	10	10	10	10
PHARMA	11	11	11	11	11
REALTY	7	8	8	7.656	8
INFRA	8	7	5	6.680	7
ENERGY	3	4	3	3.325	3
MNC	5	6	6	5.656	6

4. Conclusions

The present study explores the integration of SAW, COPRAS, and TOPSIS methods to rank the sectoral indices in NSE, which helps investors to select the right sector for investment. Furthermore, a hybrid-rank model has been proposed as the methods showed divergent results between the rankings of one MCDM method and other MCDM methods. As per the results obtained in Table 9, the quarterly returns for the resultant three best and worst-performing sectors are displayed in Figure 2 for a better understanding of the trend and performance for the given fiscal year.

The resultant rankings obtained are compared to market forces (economic and political factors) to check the MCDM methodologies' accuracy and consistency. As in this paper, the effects of two significant events, demonetization and Goods and Service Tax (GST) have been considered, the actual trends observed in the economy are compared with the results from this paper.

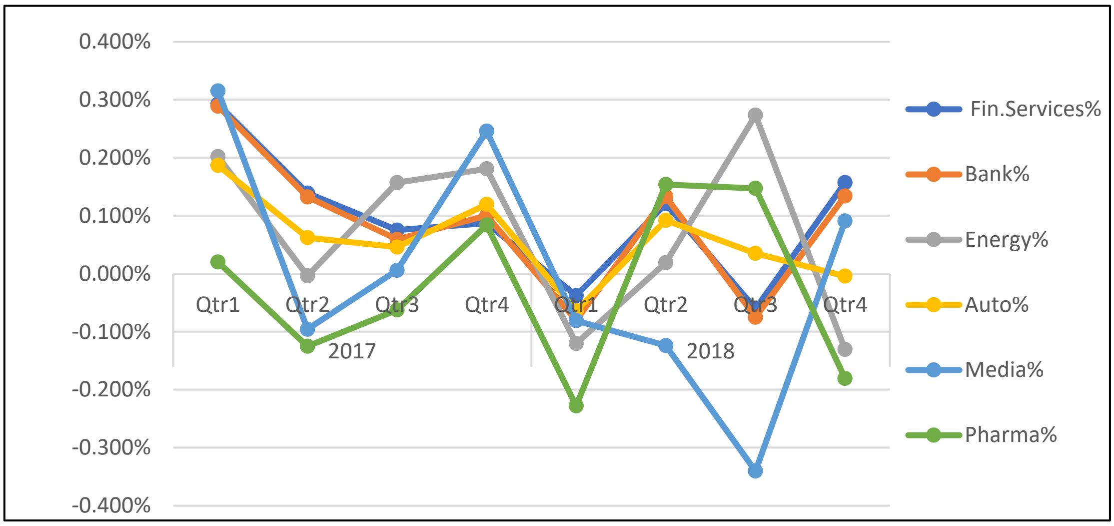

Figure 2. Returns of sectors.

The announcement of demonetization of Indian banknotes had a direct impact on the economy as Nifty went down by 1.3%, with a downward effect on all sectoral indices. More specifically, industries such as Banking, Auto, and FMCG got affected slightly greater in comparison to others. The ramifications of this announcement made in late 2016 carried on in early 2017 as the economy tried to improve and recover. It was observed that by June 2017, all the indices in the stock market marked positive trends, indicating a swift and encouraging recovery post demonetization (Tiwari and Singh, 2017). The Government announced the GST rates on May 8, 2017, which came into effect on July 1, 2017. This announcement immediately led to abnormal returns from three sectors, primarily: Pharmaceutical, Public Sector Undertaking (PSU) Bank, and Realty, which constitute 21% of the capital market (Lakshmi and Alex, 2018).

The worst indices are analyzed to correlate their downfall with the economy. Nifty Pharma performed the most poorly, owing to its 3-year low in 2017, primarily due to price erosion triggered by an increase in the US Food and Drug Administration's (FDA) approval for drugs. This directly led to increased competition and impacted their financials. The Abbreviated New Drug Application (ANDA) approvals further increased from 650 to 1,000 in the next two years. All this, in turn, led to the de-rating of the top-weighted stocks of Pharma companies (Korgaonkar, 2017; Shyam, 2017).

Similarly, the negative returns for PSU Banks were noticed due to the increase in complexity for compliance procedures and due to costlier services. Finally, the Realty sector had abnormal returns because of the now higher tax rates paid by buyers of raw materials (Reporter, 2018).

Nifty Media showed an upward trend until the end of 2017. However, it started declining from July 2018 onwards, after the launch of Jio Giga fiber by Reliance Jio. Since July 5 2018, the Nifty Media index slipped 14% after Mukesh Ambani-owned Company Reliance Jio announced their Fibre-To-The-Home (FTTH) service at Reliance Industries' 41st Annual General Meeting (AGM) (BusinessToday, 2018). The company started accepting registrations for its broadband service from August 15, 2018, which directly caused the downgrading of the important stocks listed on the index. Additionally, compounded by slower-than-expected advertising revenue growth, market share losses on account of higher competition, and higher losses for new media initiatives.

Whereas on comparison of the best indices with the economic environment, Nifty Bank had an overall upward trend throughout 2017 and 2018 due to multiple reasons. Firstly, the Government reduced the requirement of additional borrowing for the year. Secondly, it supported a low standard deviation, high returns, high volume, and high turnover average (Sinha, 2017). Even though the Indian market experienced demonetization and many other financial and political factors, it was observed that Nifty Financial Services and Nifty Bank were still ranked at the top. The primary reason is that irrespective of any amount of bank frauds and defaults, investors would not stop trusting a bank. Banks and financial services would always be the first preference to store an individual's savings. Nifty Financial services had a slightly upper edge compared to banks due to diversification as their portfolio includes banks, financial institutions, housing finance, insurance companies, and other financial services companies. Therefore, from an investor's perspective, this paper essentially evaluates how certain portfolios function and helps to understand their suitability for future investments.

A technical analysis backed by certain economic factors gives a holistic approach towards a look-back analysis of the best and the worst-performing industries. Certain sectors perform well over a particular period, whereas other sectors don't achieve high returns, a ranking of the sectors based on their recent past performance would help the investors get an idea about each sector's recent performance, which guides them to select the appropriate sector for investments. Hence this research does have an impact on the stock market, as there are several business sectors associated with the stock market, and these investments made contribute to its growth. Furthermore, the understanding of sectoral performance will help the portfolio managers, brokers and investors in fund investment and re-allocation processes. Although MCDM methods are one of the most sought-after techniques in the industry today, some limitations apply to the usability of this research. Firstly, as shown in Table 9, the rankings from different approaches are divergent to make a conclusion on the best possible index to invest in. Considering that we have taken over eleven sectors, this is highly possible due to the complexities involved with the implementation of each model (Kujawski, 2003). Hence, we consider three best and worst-performing indices (aligned in each model) to reach a recommendation for our investors. Secondly, this research would not be able to provide a predictive output for the sector performance in the future, neither does it aim to back the historical performance. The results cannot be extrapolated to either a general scenario or a pandemic situation where the metrics and criteria would be widely different.

Future research on this paper includes combining the MCDM optimization approaches along with machine learning and artificial intelligence tools to develop a model, which not only provides a look back analysis but also helps to forecasts economic decisions in a more efficient manner. Additionally, research can also be conducted in other emerging markets undergoing various public policy measures.

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Conflict of interest

The authors declare no conflicts of interest in this paper.

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