Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

A Multi Criteria Decision Making Approach To Rank Alternative Investment Indices Based On Their Performance

Prof. Jagabandhu Padhy[1], Prof. Amit Bathia[2]*, Mr. Krish Dhameja[3], Mr. Paarth Kothari[4], Mr. Saksham Agarwal[5], Mr. Tushar Sattigeri[6]

[1]Assistant Professor, NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: jagabandhu.padhy@nmims.edu
*[2]Assistant Professor,(*Corresponding Author) Atlas Skilltech University, Mumbai, India*
Email: amit.bathia@atlasuniversity.edu.in
[3]B.SC. Finance, NMIMS Anil Surendra Modi School of Commerce, Mumbai, India.
[4]B.SC. Finance, NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
[5]B.SC. Finance, NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
[6]B.SC. Finance, NMIMS Anil Surendra Modi School of Commerce, Mumbai, India

Abstract:
The selection of the ideal Alternative Investment product has been a major challenge for all investors across the world. This is because of the dynamic ever-changing financial market and the complex trade-offs between risk and return. This complexity comes from the diverse characteristics of alternative investments, where products offering high returns often come with increased volatility, while safer options provide relatively lower returns. Hence, we have adopted a Multi-Criteria Decision-Making (MCDM) model to identify the optimal investment product.

In this study, we analyse the performance of eight alternative investment products (AIPs) — including S&P 500, Hedge Funds, Venture Capital, Private Equity, US Government Bonds, MSCI Emerging Markets, FTSE EPRA/NAREIT, and S&P GSCI Commodity — using three widely accepted MCDM methods: COPRAS (Complex Proportional Assessment), SAW (Simple Additive Weighting), and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). The decision matrix incorporates critical performance metrics such as Standard Deviation, Mean Return, Skewness, Kurtosis, Beta, Sharpe Ratio, Sortino Ratio, and Calmar Ratio.

To assign weights to these criteria we used the Analytic Hierarchy Process (AHP) to ensure a balanced evaluation. The rankings generated by these methods are often a little different, that is why we used a hybrid-ranking approach through Spearman's Rank Correlation to consolidate the final rankings.

Our findings indicate that Hedge Funds and Venture Capital emerge as the most attractive options for investors seeking high returns, while US Government Bonds and FTSE EPRA/NAREIT provide safer alternatives with lower volatility. This MCDM framework offers investors a systematic and efficient method to evaluate and rank AIPs to make informed decisions in this complex financial landscape.

Keywords: MCDM, Alternate Investment, COPRAS, SAW and TOPSIS

Introduction
The role of alternative investment markets in portfolio diversification remains essential by introducing assets which exceed stocks and bonds in investor investment portfolios. Alternative investments take place across hedge funds and private equity together with real estate commodities and venture capital investors who operate under diverse economic, political and financial elements. The evaluation methods for alternative investments differ from traditional asset/portfolio evaluation because they showcase unique risk-return patterns and need specialized analytical models for proper assessment

(Markowitz, 1952; Gupta et al., 2021). Multiple Criteria Decision-Making (MCDM) approaches function as efficient evaluation tools to rank alternative investment selections through combined financial metric analysis (Hwang & Yoon, 1981).

The study focuses on applying MCDM approaches for ranking multiple investment indices active in U.S. financial markets. Analysis will rely on the specified indices to determine rankings.

- S&P 500 MSCI Emerging Markets
- JPM US Government Bonds
- FTSE EPRA Nareit
- S&P GSCI Commodity
- Eureka Hedge Fund Index
- FTSE PE Buyout Index
- FTSE Venture Capital

The performance assessment for these alternative investment indices depends on Mean and Standard Deviation statistics along with Kurtosis and Skewness calculations and incorporates Beta value measurement and evaluations of Calmar Ratio as well as Sharpe Ratio and Sortino Ratio. A structured transparent ranking system helps investors detect their best alternative investment opportunities by risk-adjusted returns through the combination of Complex Proportional Assessment (COPRAS) Simple Additive Weighting (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS methodology (Zavadskas et al., 1994; Gupta et al., 2021). Research gains its importance because it generates analytical data about alternative investments that helps investors select their best portfolio strategies embedded in complex financial systems. Economic events along with risk analysis form the basis of a systematic method which enables index selection based on a systematic approach for investors. This paper studies MCDM applications in financial decision operations then proceeds with a fundamental explanation of ranking investment index methodologies before presenting research findings and ending with essential remarks for investors.

Literature Review

There are several studies conducted that have looked into the fundamental constituents influencing alternate investment markets by understanding investor sentiments and assessing their performance. We will examine earlier studies performed by researchers to analyse various alternate investments and trends in their movements in US markets. Gupta, Parikh and Datta (2021) use MCDM (Multi-Criteria Decision Making) to rank various sectoral stock indices of the national stock exchange of India based on their performance. The paper uses AHP (Analytic Hierarchy Process), COPRAS (Complex Proportional Assessment Method), SAW (Simple Additive Weighting) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to come to a conclusion. The results show that the financial services sector and banking sector are the most optimal sectors for investment purposes, with the Media and Pharmaceutical sectors being the least optimal. Poklepović & 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. Roy (2024) conducts a study on alternate investments in India and draws out descriptive statistics and inferential statistics. He concludes that Venture Capital (18.5%) and Private Equity (15.1%) are the type of alternate investments which provide the highest returns in India as well as discovering that the top 10% of alternate investment funds have an average return of 20.5%. Kadapure and Rathod (2024) talks about tools of MCDM such as AHP and TOPSIS along with their various advantages, disadvantages and uses. Türegün (2022) shows us the application of Multi-Criteria Decision-Making (MCDM) techniques, specifically TOPSIS and VIKOR, to evaluate the financial performance of tourism companies listed on the Borsa Istanbul. An entropy method is utilised to determine criteria weights, providing a framework for ranking companies based on multiple financial metrics. The findings reveal similar rankings between TOPSIS and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) in 2018 and 2019, with some variations in 2020. Bermejo, Figuerola-Ferretti, Hevia and Santos (2021) investigate the performance of investing strategies applied to European high-capitalization corporate data from 1991-2019. They demonstrate that systematic active management portfolios, based on value, profitability, and momentum factors, can outperform benchmark strategies in the European market.

Financial markets have broadly explored MCDM techniques for evaluating and ranking stocks, mutual funds, sectoral indices, etc. Nonetheless, their use in ranking alternative investment indices is a rising research area. Alternative investments are those which have a low correlation with stock and bonds. Generally, this includes investments like private equity, hedge funds, real estate, commodities, and venture capital (Gupta et al., 2021). Since these indices are difficult to value, MCDM is a useful tool to measure their performance.

Many researchers rank financial asset using MCDM Methods SAW, COPRAS, and TOPSIS refer to analyzing multiple performance yardsticks as Zavadskas et al. (1994) and Hota et al. (2018). In other words, MCDM can be applied to the financial sector as shown by Gupta et al. (2021) who carried out the assessment of private sector banks. Likewise, Poklepović and Babić (2014) managed to select the optimal stocks by using a hybrid MCDM model. The findings indicate that using a combination of ranking techniques is useful as it enhances the reliability of decision-making.

MCDM is a method that can integrate different financial indicators, including Sharpe ratio, Sortino ratio, Calmar ratio, mean return, standard deviation, beta, skewness, among others, for the generation of a ranking system relative to alternative investment indices (MCDM, 2020). These factors help investors judge alternative indices based on risk-adjusted returns and other stability factors. Due to the complexity of alternative assets, MCDM can help institutional investors who want a data-driven method for selecting assets (Pineda et al., 2018).

Macroeconomic conditions, policy changes, and global crises have a major impact on alternative investment indices. Compared to traditional stock indices that see a change mainly only because of corporate performance and market conditions, alternative investments are more affected by geopolitical uncertainty, regulatory changes, and economic disruptions.

For example, the oil price crash from 2015 to 2016 affected commodity investments that changed expectations of risk-return from energy-origin indices (Hamilton, 2016). The Brexit incidence in 2016, is another instance which impacted firmness in the European real estate and private equity markets' long-term valuations (Dhingra et al., 2017). Examination of financial crises illustrates how alternative investments suffer from adverse external shocks. The U.S.-China trade war began in 2018 and led to huge fluctuations in global bond markets and hedge funds due to supply chain issues and tariff measures. In the same manner, the COVID-19 pandemic (2020–2021) has changed the investment landscape by boosting demand for risk-averse investments such as gold and government bonds at the expense of private equity and real estate indices. In more recent times, the Russia-Ukraine conflict is driving commodity price volatility and affecting alternative investments (Smialek, 2022).

Regulatory choices likewise have a big impact on alternative investment performance. Since 2022-2023, the interest rate hike action by Federal Reserve (Bernanke, 2022) had an impact on bond yields and equity markets that impacted institutional investment strategies in alternative investments. The emergence of ESG investing resulted in altering the existing framework for ranking alternative investments (Marqués et al., 2020). Due to market condition changes, MCDM can help to evaluate how macroeconomic factors impact the alternative investment indices. Even with its benefits, MCDM poses many problems with alternative investment indices. A big flaw is the subjectivity of weights given to financial criteria which gives rise to inconsistency of ranking by different methods (Kujawski, 2003). Choosing the weights requires some calibration since the return patterns and liquidity constraint of alternative investments are quite diverse. MCDM systems are mostly used as retrospective assessment systems and not as predictive systems. While it does help rank investment indices on the basis of past performance, it does not offer any future performance forecast. To overcome this limitation, there is a need to combine MCDM with artificial intelligence (AI) and machine learning (ML) (Gupta et al., 2021). MCDM frameworks now can benefit from adaptive MCDM approaches that utilize AI based models for ranking criteria based on real-time data (Marqués et al., 2020).

The future of MCDM based ranking for alternative investments will likely be the use of hybrid models as opposed to MCDM methods used to date. Using this method, efficiency in ranking will improve, subjectivity will be reduced and decision making will be enhanced. As digital assets like cryptocurrencies and tokenized securities become more popular, MCDM methodologies must change to include the unique characteristics of these alternative ways to invest.

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.

Index selection framework

The information used for this study comes from several financial market databases such as Bloomberg, MSCI, and S&P Dow Jones Indices. It captures performance data of alternative investment indices for the timeframe of January 1, 2015, to December 31, 2024, and includes a broad range of asset classes including private equities, hedge funds, real estate, commodities, and venture capital. This dataset includes the daily returns, volatility measurements, and trading volume averages for the chosen indices over the sample timeframe. Besides, to allow for a complete multi-criteria ranking of alternative investments, key financial parameters such as Sharpe ratio, Sortino ratio, Calmar ratio, standard deviation, beta, and skewness have been added.

Methods

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.

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 alternative 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

$$= [\quad]_{m\times n}^{ij} \qquad (1)$$

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:

$$= [r_{ij}]_{m\times n} \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad (2)$$

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

$$= [\ _{ij}]_{m\times n} = \ _{ij}. \ _j, \quad = 1, 2, \ldots, \ ; \quad = 1, 2, \ldots\ldots, \qquad (3)$$

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:

$$\sum_{i=1}^{m} \ _{ij} = \ _j, \quad = 1, 2, \ldots, \qquad (4)$$

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

$$_{+i} = \sum_{j=1}^{n} \ _{+ij}, \quad _{-i} = \sum_{j=1}^{n} \ _{-ij}, \quad = 1, 2, \ldots, \qquad (5)$$

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

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

$i.$

where S-min is the minimum value of S-

(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.

$$U_i = \frac{Qi}{Qmax} . 100\% \tag{7}$$

In the above, Qmax is the maximum relative preference value.

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).

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

$$= [\quad]_{m\times n}^{ij} \tag{8}$$

where xij 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.
(6) Determining the ideal and negative ideal solution:
The ideal solution has the best values for each attribute:

$$^{+} = \{(\max\ _{ij} \mid\ \in\ ).(\min\ _{ij} \in\ '),\quad = 1, 2, \dots,\ \} = \{\ _{1}^{+},\ _{2}^{+}, \dots,\ _{n}^{+}\} \tag{9}$$

where J is a set of benefit attribute indices, and J' is a set of cost attribute indices. The negative ideal solution:

$$^{-} = \{(\min\ _{ij} \mid\ \in\ ).(\max\ _{ij} \in\ '),\quad = 1, 2, \dots,\ \} = \{\ _{1}^{-},\ _{1}^{-}, \dots,\ _{n}^{-}\} \tag{10}$$

Therefore, it can be inferred that these alternatives inside the offered set of alternatives will not exist.
(7) 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 Xj) by the norm of that vector. Column vectors in the decision matrix then become:

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

(8) Measuring the distance:

$$= \{\ _{1},\ _{2}, \dots,\ _{n}\} \tag{12}$$

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

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

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

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

$$= \frac{S_i^-}{S_i^+ + S_i^-} \qquad (15)$$

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.

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.

Data and Results

Data

In this paper, we have ranked and analysed eight alternative investment products and ranked them using different MCDM techniques. The indices and products selected for analysis include S&P 500, MSCI Emerging Markets, US Government Bonds, FTSE EPRA/NAREIT, S&P GSCI Commodity, Hedge Fund, Private Equity, and Venture Capital. The decision criteria used to evaluate these indices are Standard Deviation, Mean Return, Skewness, Kurtosis, Beta, Sharpe Ratio, Sortino Ratio, and Calmar Ratio.

- Standard Deviation: Measures the volatility of returns.
- Mean: Represents the average return over the period.
- Skewness: Assesses the asymmetry of return distribution.
- Kurtosis: Evaluates the fat tails or extreme deviations from the mean.
- Beta: Reflects the sensitivity of the asset to market movements.
- Sharpe Ratio: Indicates the risk-adjusted return.
- Sortino Ratio: Similar to the Sharpe Ratio but focuses only on downside volatility.
- Calmar Ratio: Measures the return relative to the maximum drawdown.

Firstly, we obtain each indice daily return and then calculate daily mean return and daily standard deviation. 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 the S&P 500. The Sharpe ratio was used to measure the risk adjusted returns. Risk adjusted returns means returns above the daily risk free rate.First the daily mean return was subtracted from the daily risk free rate. We then dividend this by the daily standard deviation to obtain Sharpe ratio. We also calculated Sortino Ratio which also measures risk adjusted returns but only considers downside deviation. We also used the daily mean return to calculate kurtosis and skewness. Skewness was used to measure the asymmetry of data from normal distribution. A positive skewness indicates that majority of the values are concentrated on the left with a few positive outliers. A negative skewness indicates majority of the values are concentrated on the right with a few negative outliers. Kurtosis is a statistical measure that describes the shape of a distribution compared to a normal distribution. It tells us how extreme the outliers are in the data set. A kurtosis value of 3 indicates the data is normally distributed and has no extreme outliers. A kurtosis value above 3 indicates the data set is leptokurtic, means it has a more values closer to the mean and more extreme outliers indicated higher risk. A kurtosis value below 3 indiactes the data set is platykurtic, means it has uniform distribution and few extreme outliers, meaning lower risk and lower chance of extreme volatility. To calculate calmar ratio we first calculated CAGR(Compounded annual growth rate) and Maximum Draw Down. Maxmium drawdown measures the largest peak to trough decline before it recovers. Calmar ratio is CAGR divided by Maximum Draw Down, measures performace relative to risk. The low calmar ratio must be due to the crash during Covid-19. It should be noted that selected indices belong to different alternate investment classes. The initial data of the study has been given in Table 1. It includes 8 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 1. Decision Matrix

Decision Matrix										
Indices/ Parameters	Standard Deviation	Mean	Skewness	Kurtosis	Beta	Sharpe Ratio	Sortino Ratio	Calmar Ratio	MDD	CAGR
S&P 500	1.123	0.055	-0.525	14.563	1.000	0.049	0.069	0.176	74.33%	13.10%
MSCI Emerging Markets	1.019	0.010	-0.361	4.225	0.378	0.010	0.013	0.023	52.35%	1.21%
US Government Bonds	0.321	0.004	0.059	3.298	-0.051	0.013	0.018	0.044	20.79%	0.92%
FTSE EPRA/NAREIT	1.312	0.031	-1.132	21.161	0.858	0.023	0.032	0.104	54.65%	5.68%
S&P GSCI Commodity	1.427	0.015	-0.622	6.501	0.386	0.011	0.015	0.019	70.91%	1.31%
Hedge Fund	0.197	0.024	0.086	0.225	0.012	0.124	0.196	0.132	47.66%	6.27%
Private Equity	1.808	0.058	-0.267	19.796	1.542	0.032	0.045	0.154	71.85%	11.06%
Venture Capital	2.200	0.096	-0.362	5.932	1.695	0.044	0.061	0.227	87.02%	19.71%

Source: Authors work from excel

Results

The decision matrix highlights how risk-return profiles differ across asset classes. For example, the S&P 500 and Private Equity have Sharpe Ratios that are high enough to suggest they deliver returns that are risk adjusted better than others. But that given high-risk characteristic, Venture Capital has the greatest Standard Deviation. This table shows that the US Government Bonds have the smallest deviation and the least beta associated with them, confirming their status as low-risk assets. In contrast, Private Equity and Venture Capital have the highest standard deviation and beta; thus, they are greater in volatility and sensitivity to market fluctuations. The Sortino and Calmar Ratios provide additional risk-adjusted insights. Hedge Funds and Venture Capital show relatively higher Sortino Ratios, indicating better downside risk management. However, MSCI Emerging Markets and S&P GSCI Commodity exhibit lower Sharpe and Sortino Ratios, suggesting that they may not be the most efficient options for risk-adjusted returns. This decision matrix forms the basis for the AHP weight assignment and multi-criteria decision-making (MCDM) analysis that follows.

Table 2. AHP results

AHP RESULTS								
TOTAL	Standard Deviation	Mean	Skewness	Kurtosis	Beta	Sharpe Ratio	Sortino Ratio	Calmar Ratio
1	0.083	0.267	0.043	0.043	0.083	0.160	0.160	0.160

Source: Authors work from excel

As we can see above in Table 2 above daily mean return has been given the most importance as investors usually care the most about gross return. Sharpe, Sortino and Calmar have been given the second most importance due to their ability to measure risk adjusted returns. Standard deviation and Beta have lower importance to investors as daily deviation is not an issue in alternate investment as investors are investing for long term. The results obtained by COPRAS, SAW and TOPSIS approaches are displayed in Table 3,4,5 respectively.

Table 3. COPRAS results

COPRAS RESULTS						
Nifty Indices/ Parameters	Sum of beneficial criteria (Si+)	Sum of non beneficial criteria (Si-)	S-min/Si	Qi	Ui (Utility)	Rank
S&P 500	0.133	0.040	0.022	0.137	38.06%	3
MSCI Emerging Markets	0.023	0.022	0.040	0.030	8.42%	8
US Government Bonds	0.025	0.003	0.273	0.074	20.53%	5
FTSE EPRA/NAREIT	0.070	0.051	0.017	0.073	20.45%	6
S&P GSCI Commodity	0.028	0.030	0.028	0.033	9.29%	7
Hedge Fund	0.181	0.001	1.000	0.359	100.00%	1
Private Equity	0.114	0.053	0.016	0.117	32.48%	4
Venture Capital	0.173	0.052	0.017	0.176	49.00%	2

Source: Authors work from excel

Table 4.SAW results

SAW RESULTS										
Nifty Indices/ Parameters	Standard Deviation	Mean	Skewness	Kurtosis	Beta	Sharpe Ratio	Sortino Ratio	Calmar Ratio	Sum	Rank
S&P 500	0.042	0.154	-0.260	0.029	0.049	0.064	0.056	0.125	0.259	4
MSCI Emerging Markets	0.039	0.028	-0.179	0.009	0.019	0.013	0.011	0.016	-0.046	6
US Government Bonds	0.012	0.012	0.029	0.007	-0.002	0.017	0.015	0.031	0.120	5
FTSE EPRA/NAREIT	0.050	0.085	-0.561	0.043	0.042	0.030	0.026	0.074	-0.212	8
S&P GSCI Commodity	0.054	0.043	-0.309	0.013	0.019	0.014	0.012	0.013	-0.140	7
Hedge Fund	0.007	0.068	0.043	0.000	0.001	0.160	0.160	0.093	0.533	1
Private Equity	0.068	0.162	-0.132	0.040	0.076	0.042	0.037	0.109	0.401	3
Venture Capital	0.083	0.267	-0.179	0.012	0.083	0.057	0.050	0.160	0.533	2

Source: Authors work from excel

Table 5. TOPSIS results

TOPSIS RESULTS				
Nifty Indices/ Parameters	Si+	Si-	RC	Rank
S&P 500	0.271	0.313	0.536	6.000
MSCI Emerging Markets	0.053	0.554	0.912	3.000
US Government Bonds	0.045	0.566	0.927	2.000
FTSE EPRA/NAREIT	0.566	0.095	0.144	8.000
S&P GSCI Commodity	0.082	0.520	0.864	4.000
Hedge Fund	0.023	0.581	0.962	1.000
Private Equity	0.504	0.088	0.148	7.000
Venture Capital	0.147	0.520	0.779	5.000

Source: Authors work from excel

We obtain the ranks from each of the MCDM procedures. From the above Tables there seems to be overlapping of ranks for the various indices. These tables provide for the weights of each criterion. The weights for further calculations are obtained through the AHP method. After which, the ranks have been calculated for the three MCDM methods on the basis of the decision matrix and weights.

After gaining the rankings from different MCDM methods, we applied the Spearman's rank correlation coefficient method to resolve the contradiction stemming from the divergent rankings. Thus, a single hybrid rank for all sectors is derived on the basis of which the best-performing sector is recommended.

Table 6 below gives an overview of the Spearman's rank correlation coefficients between the rankings of the three MCDM methods. It was the basis for calculating the weights and normalized weights. Write the rank of TOPSIS, SAW and COPRAS between each other.

Table 6. Spearman's Correlation Coefficient

Spearman's Correlation Coefficient			
	TOPSIS	SAW	COPRAS
TOPSIS	1.000	0.333	0.119
SAW	0.333	1.000	0.881
COPRAS	0.119	0.881	1.000

Source: Authors work from excel

Table 7. Spearman's Ranking

Spearman's Ranking			
Best Approach	TOPSIS	SAW	COPRAS
Normalised Weights	0.300	0.374	0.327
Ranks	3.000	1.000	2.000

Source: Authors work from excel

With the normalized weights acquired as illustrated, the hybrid-MCDM ranking approach is employed for identifying the best sectors for investment. The weighted score is being computed utilizing the ranking and normalized weights obtained from each of the MCDM approaches. This calculation is pretty much similar to that of calculating the expected portfolio return or volatility on the assets given:

Weighted Score = (NWTOPSIS * RankTOPSIS) + (NWSAW * RankSAW) + (NWCOPRAS * RankCOPRAS)

NW here stands for Normalized Weight, whereas Rank is the respective rank of the sector in each MCDM method. The final rank is exhibited in the table below.

Table 8. Final Ranking

Final Ranking					
Indices / MCDM Ranks	TOPSIS RANK	SAW RANK	COPRAS RANK	Weighted Score	Final Rank
S&P 500	6	4	3	4.272	4
MSCI Emerging Markets	3	6	8	5.755	6
US Government Bonds	2	5	5	4.101	3
FTSE EPRA/NAREIT	8	8	6	7.347	8
S&P GSCI Commodity	4	7	7	6.101	7

Hedge Fund	1	1	1	1.000	1
Private Equity	7	3	4	4.525	5
Venture Capital	5	2	2	2.899	2

Source: Authors work from excel

Conclusion

The study explores integration of SAW, COPRAS and TOPSIS methods to rank various alternate investment indices of the USA, which helps investors to select the right sector for investment. Along with that, a ranking model in Table 8 has been proposed to show the difference in rankings across the various MCDM methods. All the selected alternate investment indices are displayed in Figure 1 for a better understanding of the 5-year growth trend and performance.

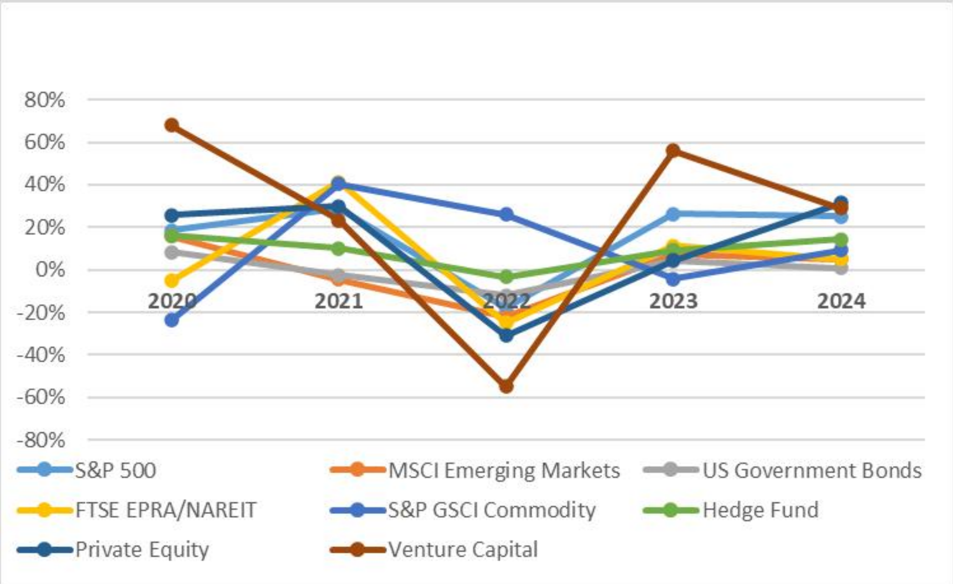

Figure 1: Yearly returns of alternate investment class

The performance of the alternative investment products that we included is closely linked with the macroeconomic condition of the US economy. The COVID-19 pandemic brought havoc on the US economy and contraction made way for the Federal Reserve to introduce large stimulus packages and cut interest rates. Recovery in the S&P 500 and Venture Capital markets was swift, while US Government Bonds were in demand as a safe haven. On the other hand, demands for Commodities and Real Estate (FTSE EPRA/NAREIT) dipped owing to waning demand and commercial activity. The U.S. economy grew by 5.7% in GDP in the year 2021, fueling further chances of venture capital and private equity investments in the industry by the huge investments made in technology and digital transformation, but in 2022 US had the highest inflation levels so far recorded. Interest rates made the Federal Reserve also must raise them aggressively as equity markets-from the very S&P 500 to those of venture capital and private equity-hiked their ruled down prices while commodities did otherwise with rising energy prices. With the gradual cooling of inflation in 2023, S&P 500, private equity, and venture capital entered another boom, tied to different advancements in technologies associated with both renewable energies and AI. Except for a few minor squabbles here and there, by the year 2024, the US economy stabilized regarding interests and most alternative investments were showing steady performance, hedge funds, some government bonds and commodities being price correction phase.

These then speak volumes as to how the different alternate investment products react to the changing economic environment, inflationary pressures, and shifts in interest rates. Venture Capital and Private Equity thrive during periods of technological innovation and economic growth but are highly sensitive to interest rate fluctuations. S&P 500 closely mirrors broader market trends, while US Government Bonds provide stability during economic downturns. Understanding these correlations helps investors diversify their portfolios and align their investment strategies with prevailing macroeconomic conditions.

Certain alternate investments perform well over a period, whereas others do not achieve high returns. A ranking of these investments would help investors get an idea about each alternate investment indices performance and make better decisions when choosing where to invest. This research has an impact on the alternate investment market, helping investors, brokers, portfolio managers in asset allocation, rebalancing, etc. Although MCDM methods are very useful in the investment industry, they do have their limitations. Firstly, as shown in Table 8, the rankings using SAW, COPRAS and TOPSIS produce divergent rankings for the best alternate investment index to invest in. Secondly, this paper cannot predict future performance for these indices or support their historical performance.

Future Research Agenda

The current study successfully applied Multi-Criteria Decision-Making (MCDM) techniques including TOPSIS, COPRAS and SAW to rank different alternative investment products and indices. While the study provides a comprehensive evaluation framework, there remain several unexplored areas that future research can address to enhance the applicability of MCDM techniques in financial decision-making.

- Dynamic Criteria and Time-Based Analysis

The financial market is dynamic, and the performance of alternative investment products varies with time. Future studies should entail some considerations on the time-varying application of such techniques to capture changing trends with investor sentiment. This will also allow one to harness the capability of using dynamic MCDM models to understand better the varying rankings of alternative investment products in different market cycles.

- Inclusion of ESG (Environmental, Social, and Governance) Parameters

Considering the rising significance of sustainable investing, future studies should look into introducing ESG factors as further criteria in the decision matrix. Considering alternate investment products through the lens of sustainability will enable investors to position their portfolios toward ethical and environmentally friendly investment practices. Inclusion of ESG (Environmental, Social, and Governance) Parameters

- Use of Machine Learning and AI in MCDM Models

The application of machine learning (ML) and artificial intelligence (AI) in MCDM frameworks will help to automate and refine the manual decision-making process.

References

1. Gupta, R., & Kumar, S. (2021). Application of MCDM in banking and stock selection.
2. Hwang, C.-L., & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications*.
3. Markowitz, H. M. (1952). Portfolio selection.
4. Zavadskas, E., Turskis, Z., & Kildienė, S. (1994). COPRAS method application in MCDM problems for financial decision-making processes.

5. Roy, S. N. (2024). The Role of Alternative Investments in Diversified Portfolios: A Study of Returns, Risk, and Correlation, Taking Examples Under Indian Context. *International Journal of Research Publication and Reviews, 5*(8), 3789-3804
6. Kadapure, P., Rathod, P., & Roopa, K. (2024). A Review on Application of Multi-Criteria Decision Making Approaches. *Acta*, *Volume*, *Pages*.
7. Türegün N. (2022). Financial performance evaluation by multi-criteria decision-making techniques. *Heliyon*, *8*(5), e09361.
8. Bermejo, R., Figuerola-Ferretti, I., Hevia, T., & Santos, A. (2021). Factor investing: A stock selection methodology for the European equity market. *Heliyon*, *7*(10), e08168.
9. Gupta, D., Parikh, A., & Datta, T. K. (2021). A multi-criteria decision-making approach to rank the sectoral stock indices of national stock exchange of India based on their performances. *National Accounting Review*, *3*(3), 272-292.
10. Poklepović, T., & Babić, Z. (2014). Stock selection using a hybrid MCDM approach. *Croatian Operational Research Review*, *5*, 273-290.
11. Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). COVID-induced economic uncertainty. *National Bureau of Economic Research.*
12. Bernanke, B. (2022). Monetary policy in a new era: Challenges and implications. *Brookings Institution Press.*
13. Bown, C. P. (2020). The 2018–2019 trade conflict with China: An evaluation. *Peterson Institute for International Economics.*
14. Dhingra, S., Ottaviano, G., Sampson, T., & Van Reenen, J. (2017). The consequences of Brexit for UK trade and living standards. *Centre for Economic Performance.*
15. Gupta, S., Mathew, M., Gupta, S., & Singhal, K. (2021). Benchmarking private sector banks in India using MCDM. *Journal of Public Affairs, 21*(2), e2409.
16. Hamilton, J. D. (2016). Oil prices and stock market volatility. *Energy Economics, 53*, 59–69.
17. Hota, H. S., Awasthi, V. K., & Singhai, S. K. (2018). Comparative analysis of AHP and its integrated techniques applied for stock index ranking. *Advances in Intelligent Systems and Computing, 127*, 134–140.
18. Kujawski, E. (2003). Multi-Criteria Decision Analysis: Limitations, Pitfalls, and Practical Difficulties. *INCOSE International Symposium, 13*(1), 1169–1176.
19. Marqués, A. I., García, V., & Sánchez, J. S. (2020). Ranking-based MCDM models in financial management applications: Analysis and emerging challenges. *Progress in Artificial Intelligence, 9*(2), 171–193.
20. Pineda, P. J. G., Liou, J. J., Hsu, C. C., & Tzeng, G. H. (2018). An integrated MCDM model for improving airline operational and financial performance. *Journal of Air Transport Management, 68*, 103–117.
21. Smialek, J. (2022). How the Russia-Ukraine war is reshaping global markets. *The New York Times.*
22. Zavadskas, E. K., Kaklauskas, A., & Sarka, V. (1994). The new method of multicriteria complex proportional assessment of projects. *Technological and Economic Development of Economy, 1*, 131–139.