Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

Portfolio Optimisation for Retail Investors in the Indian Market: An MCDM Approach

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ABSTRACT

This study aims to create an optimal portfolio for retail investors investing in the Indian Markets through utilising MCDM methodologies to rank and select investments balancing maximum returns with minimal risk. This study incorporates six MCDM methods including Entropy for weighing purposes and TOPSIS, WASPAS, COPRAS, SAW, PROMOTHEE for ranking and decision making. The approach prioritizes 3 asset classes for investments that are Equity, Debt & Commodities. The ranking and selecting the ideal assets for investment in multiple asset classes will be useful for individual retail investors. The multiple quantitative and decision-making analyses run may also aid future analysts for further research. This study intends to aid retail investors for navigating investments in the Indian Markets while focusing on returns and risk.

Keywords – Portfolio Building and Optimisation, MCDM, Modern Portfolio Theory, Stock Market, Debt Market, Commodities, Excel

1. INTRODUCTION

Retail investors are individuals who are not financial professionals and trade securities in the market. These investors have surged in recent years in the Indian markets following the COVID-19 pandemic that digitalised a lot of financial services including brokers. According to NSE data, more than 120 million investors were registered over the five-year period from 2019 to 2023. Additionally, BSE data as of February 9, 2024, indicates that the number of registered retail investors had reached nearly 161 million. The introduction of user-friendly trading apps has made getting into the stock market more accessible and possible for retail investors especially for the younger generation of India (Kakkar, 2024). This convenience, along with the availability of proper educational resources and market guidance, enables them to invest with confidence. Historically, Indians have favored bank deposits for their savings, viewing them as safer and more stable compared to the stock market, which is often seen as volatile and complex. However recent trends indicate a shift where young investors are more willing and adamant on learning and investing in the stock market to diversify their portfolio beyond traditional assets (A Ksheerasagar, 2024). A few decades ago, the classical financial analysis was followed for investing in assets. Traditional financial analysis focused on the concept of assessing the value of individual asset investments. The prevailing belief was that investors should allocate their funds to assets that promise the highest future value relative to their current price. It formulated the financial decision-making process as an optimization problem (Kolm et al., 2014). However, the modern portfolio theory focussed on diversifying the portfolio, investing in multiple assets, to lower risk and maximise returns, where there is one efficient portfolio of assets and other portfolios are inefficient. (Markowitz, 1991) This method has been very popular since then and is widely followed for portfolio optimisation. Portfolio optimization is a structured mathematical method used to guide investment decisions across a range of financial assets or instruments. Portfolios are points from a feasible set of assets that constitute an asset universe. (Portfolio Optimization, n.d.) This research paper also uses the modern portfolio theory, to optimise the portfolio of retail investors among different commodities like gold, silver, copper and aluminium.

However, the modern portfolio theory has a drawback, that it only minimises risks and maximises returns. It does not consider other factors than can be crucial when building the optimal portfolio. Therefore, MCDM is used to compare and rank the stocks in NIFTY 500 and 350 corporate bonds. MCDM is among the most precise methods for decision-making. MCDM offers a framework for addressing decision-making problems and helps derive preferences from various alternatives. The stocks in Nifty 500 were analysed based on factors mentioned in Table 1. Credit rating from CRISIL and coupon rates of the bonds were used to compare and rank the corporate bonds (C.-Y. Lee, n.d.). Different methods of MCDM were performed in Microsoft Excel to get the rankings of the stocks and the corporate bonds.

These methods are Entropy Weight Method, Weighted Aggregate Sum Product Assessment Method (WASPAS), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Simple Additive Weighting (SAW), Complex Proportional Assessment (COPRAS) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE).

The analysis utilizes several MCDM methods to rank equity stocks based on the 9 ratios outlined in Table 1.

Ratios	Notations	Reference
Current Market Price to Book Value	CMP/BV	(Türegün, 2022)
Return on Equity	ROE	(Aldalou & Perçin, 2020)
Debt to Equity	D/E	(Türegün, 2022)
Dividend Yield	D/Y	(BAĞCI & YERDELEN KAYGIN, 2020)
Current Market Price to Sales	CMP/S	(Türegün, 2022)
Operating Profit Margin	OPM	(Aldalou & Perçin, 2020)
Net Profit Margin	NPM	(Aldalou & Perçin, 2020)
Return on Asset	ROA	(Aldalou & Perçin, 2020)
Dividend Payout	D/P	(BAĞCI & YERDELEN KAYGIN, 2020)

Table 1 Equity Ratios for analysis (Author's own work)

2. LITERATURE REVIEW

Multi-Criteria Decision-Making (MCDM) is a vital concept extensively studied across various fields, aiming to select the best alternative by considering multiple criteria (Taherdoost & Madanchian, 2023). It plays a crucial role in finance by providing methodologies to evaluate financial performance accurately and make informed decisions based on both qualitative and quantitative information (Almeida-filho et al., 2020). The application of MCDM in financial decision-making has gained significant attention over the years due to its ability to handle the complexity and multiple objectives inherent in financial problems, contributing to more reliable evaluations and predictions in various financial applications (Marqués et al., 2020). These techniques are utilized in evaluating financial performance in sectors like banking (Trung et al., 2024), detecting financial fraud (Taher & Nassar, 2020) and assessing financial performance in manufacturing industries (Abdel-basset et al., 2020) including business valuation (Liachovicius et al., 2020). The integration of Multiple Criteria

Decision Making (MCDM) methodologies in finance is crucial for enhancing decision-making processes and improving the quality of financial decisions (Baydaş, 2022;Hallerbach & Spronk, 2019). MCDM is essential in portfolio construction, helping select projects or assets that meet strategic goals and constraints. Building a portfolio involves creating a diverse mix of investments, such as stocks, bonds, and other assets, to meet financial objectives. Investors analyse financial statements, calculate growth indexes, assess future profits, and evaluate stock price crash risks to improve performance (Ciliberti & Gualdi, 2020). This process is essential for spreading risk, maximizing returns, and achieving a risk-reward balance (Zhong, 2022). Proper portfolio construction significantly impacts investment outcomes. It improves metrics like the Sharpe Ratio, reduces sector exposures, minimizes volatility fluctuations, and mitigates skewness and tail correlation with the market (Ciliberti & Gualdi, 2020). Additionally, Research and Development (R&D) Project Portfolio Selection (PPS) in various industries has been enhanced through MCDM methods, highlighting the importance of systematic literature reviews and decision criteria in project selection processes (de Souza et al., 2021).

Empirical studies reveal a strong positive relationship between financial development and economic growth. This reciprocal causality suggests that financial development stimulates growth and vice versa (Rachidi, 2011). The combination of finance and MCDM tools can lead to improved decision quality and outcomes. Individuals in finance should recognize financial decision problems as multiple criteria decision problems (Hallerbach & Spronk, 2019). In addition, the classification of small and micro-enterprises based on financial criteria underscores the significance of financial considerations in business operations and management (TP et al., 2022). Ehrgott et al., (2004) expanded the classical Markowitz mean-variance model by including five separate goals in terms of risk and return, making use of tailor-made heuristics that would effectively deal with problems of practical scale while giving importance to individual preferences through utility functions. This laid the framework for (Bilsel, 2007) who created the fuzzy multi-criteria model for stock investment portfolios under uncertainty, focused on stocks traded at the Istanbul Stock Exchange (ISE30) index and used fuzzy PROMETHEE to select eligible companies, resulting in a diverse portfolio tailored to investor preferences and market conditions. Building on the theme of enhancing stock evaluation accuracy, (W. S. Lee et al., 2009) conducted a literature review of the Gordon model's main factors to refine the evaluation of stock price determinants. (Shen et al., 2010) extended the FScore system using fuzzy MCDM, identifying sub-factors for stock selection, and employing expert survey and DEMATEL-ANP to determine the importance and weights. The integration of traditional models with modern techniques was further explored by (Jerry Ho et al., 2011), who introduced an investment decision model that integrates CAPM, DEMATEL, and ANP, pointing out the limitations of the conventional CAPM model, which links a portfolio's projected return to its risk (beta), which is a foundation of current portfolio theory and the need for additional factors in portfolio selection. (Poklepović & Babić, 2014) suggested a combined method using Spearman's rank correlation to tackle inconsistencies among various MCDM methods. (Aldalou & Perçin, 2020) emphasised the importance of financial ratios and profitability while evaluating firms in the BIST Technology Index, using Fuzzy Shannon's Entropy (FSE) and Fuzzy Elimination and Choice Expressing Reality (FELECTRE I). Concurrently, (Paur, 2021) proposed a hybrid MCDM model under fuzziness, which incorporated a wide range of criteria and employed the fuzzy analytic hierarchy process (FAHP) to evaluate and rank portfolios through the TOPSIS method. A comparison between hybrid MCDM approach and modern portfolio theory (MPT) for stock selection, emphasising the importance of comprehensive evaluations beyond standard methodologies was performed (Vuković et al., 2020). In similar lines, (Atta Mills et al., 2020) addressed asset allocation for investors on the Shanghai Stock Exchange (SSE), proposed a hybrid MCDM approach that combined ANP and DEMATEL in a grey environment, provided ranking and weighting information for optimal portfolio selection. (Atta Mills et al., 2020) continued to explore the hybrid MCDM strategy for stock portfolio selection, using grey-DEMATEL and grey-ANP methods to prioritise Shanghai Stock Exchange-listed companies, demonstrating how grey system theory can minimise uncertainty in portfolio decisions. (Marqués et al., 2020) provided an overview of MCDM techniques in finance, with an emphasis on portfolio management, bankruptcy, and credit risk prediction, as well as a bibliometric study of relevant research trends.

Further while exploring the effectiveness of MCDM methods, (Baydaş & Elma, 2021) demonstrated the superiority of hybrid weighting combined with PROMETHEE for evaluating manufacturing companies. Complementing this, (Baydaş & Pamučar, 2022) compared seven popular MCDM methods, introducing validation criteria and identifying PROMETHEE and Faire Un Choix Adéquat (FUCA) as robust performers in financial performance evaluations. (Veeramani, 2023) have developed an innovative FIS-based indicator for stock performance. (Işık et al., 2024) have used objective and subjective MCDM techniques to rank food and beverage companies listed on the Istanbul Stock Exchange as regards their investment potentials and validated these rankings by means of reliability testing methods. The exploration of prior research on hybrid MCDM techniques for portfolio optimization reveals a rich and diverse body of work. Key studies have provided crucial insights and methodologies, laying the groundwork for the present study. This paper explores the application of MCDM methods in optimizing investment portfolios, highlighting their effectiveness and flexibility in various markets, with a particular emphasis on the Indian retail investor scenario.

3. RESEARCH METHODOLOGY AND ANALYSIS

This research paper analyses stocks from the Nifty 500 Index, 350 different corporate bonds and 4 types of commodities to invest in. 493 stocks were selected from the Nifty 500 Index downloaded from Screener.in leaving 7 of them due to insufficient data. The 4 types of commodities; Gold, Silver, Copper, and Aluminium were analysed through an Efficiency Frontier from Modern Portfolio Theory (Duggal & Shams, 2010). The data for these commodities consisted of daily spot prices from January 2010 till April 2024 collected from the Multi-Commodity Exchange (MCX). To analyse and rank 493 stocks and 350 corporate bonds Entropy was used to calculate weights for each criterion followed by WASPAS, TOPSIS, SAW, COPRAS, PROMOTHEE. The different MCDM methods allows for alternative ranks and helps in choosing ideal stocks for investors. This same process is repeated for corporate bonds in the debt market with credit ratings and coupon rate as the criteria.

3.1 Entropy Weight Method

The entropy weight method is a widely employed technique for assigning weights often paired with MCDM decision making methods that assesses variability in decision-making. The base rule is the higher the degree of dispersion, the more information can be derived from the criterion and allocate more weightage to it (Zhu et al., 2020).

In this method, m criteria and n samples are assessed and the measured value of i^{th} criteria and j^{th} sample is recorded as x_{ij}.

The first step in this method is to normalize the data to allow comparison of values which is calculated as follows:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \quad (1)$$

Then the Entropy value E_i is calculated for the i^{th} criteria using:

$$E_i = -\frac{\sum_{j=1}^{n} p_{ij} \cdot \ln p_{ij}}{\ln n} \quad (2)$$

The range for this value is between 0 and 1 and higher is considered better for weighting. The last step is to determine the actual weight for each criterion using the entropy value and the below equation where w_i signifies weight.

$$w_i = \frac{1 - E_i}{\sum_{i=1}^{m}(1 - E_i)} \quad (3)$$

Entropy was employed to determine the weights for criteria related to both equity and debt market. The derived weights are shown in Tables 2-3.

Notation	CMP /BV	ROE	D/E	D/Y	CMP /S	OPM	NPM	ROA	D/P
Weights (%)	11.80	12.68	9.66	10.51	11.59	12.66	11.65	9.11	10.34

Table 2 Equity Criteria Weights (Author's own work)

Notation	Coupon rate	Rating
Weights	4.09%	95.91%

Table 3 Debt Criteria Weights (Author's own work)

3.2 Weighted Aggregate Sum Product Assessment Method (WASPAS)

The Weighted Aggregate Sum Product Assessment method, commonly referred to as WASPAS, combines two other Multi-Criteria Decision-Making approaches: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). By combining these approaches, WASPAS aims to provide more precise results while avoiding complex mathematical equations (Chakraborty et al., 2015).

In this method, m represents the number of alternatives, n denotes the number of criteria being assessed, and x_{ij} indicates the performance of the i^{th} alternative with respect to the j^{th} criterion.

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

The first step is to normalize the data to allow comparison of values which is calculated as follows:

$$\bar{x}_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \text{ for beneficial criteria,} \quad (4)$$

$$\bar{x}_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \text{ for non-beneficial criteria,} \quad (5)$$

Where $\bar{x}_{ij}$ is the normalized value of x_{ij}. Once the normalized value is determined, a combined criterion of optimality is pursued, derived from two distinct criteria of optimality.

The first criterion of optimality is WSM, which calculates the overall relative importance of the i^{th} alternative as shown below:

$$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij}\, w_j \quad (6)$$

Where w_j represents the weight determined using the Entropy method. The other criterion of optimality is WPM to calculate the overall relative importance of the i^{th} alternative as shown below:

$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \quad (7)$$

The joint criterion of optimality combining additive and multiplicative methods is calculated from the following equation:

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)} = 0.5\sum_{j=1}^{n} \bar{x}_{ij}\, w_j + 0.5\prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \quad (8)$$

Once the final joint criterion of optimality (Q_i) is calculated for each alternative, they are ranked in the descending order meaning higher value of Q_i signifies a superior alternative as compared to the others. The final top 20 rankings for both stocks and corporate bonds as analysed are presented in Tables 4-5.

Rank	Name	Industry
1	Authum Investments	Financial Services
2	IDFC Bank	Financial Services
3	Tata Teleservices Maharashtra	Telecommunication
4	Bajaj Holdings	Financial Services
5	Lloyds Metals	Metals & Mining
6	Nippon Life India AMC	Financial Services
7	UTI AMC	Financial Services
8	HDFC AMC	Financial Services
9	Sun TV Network	Media Entertainment & Publication
10	ITC	Fast Moving Consumer Goods
11	Indian Energy Exchange	Financial Services
12	Oracle Financial Services	Information Technology
13	P & G Hygiene	Fast Moving Consumer Goods
14	CDSL	Financial Services
15	Colgate-Palmolive	Fast Moving Consumer Goods
16	Glenmark Life Sciences	Healthcare
17	Embassy Office Parks REIT	Financial Services
18	Tata Investment Corporation	Financial Services
19	Gujarat State Petronet	Oil Gas & Consumable Fuels
20	Coal India	Oil Gas & Consumable Fuels

Table 4 WASPAS Equity Rankings (Author's own work)

Rank	Name
1	NTPC Limited CRISIL AAAINE733E07CB1
2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2
3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
4	Poonawalla Fincorp Limited CRISIL AAAINE511C08985

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5	Poonawalla Fincorp Limited CRISIL AAAINE511C08AD3
6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6
7	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8
8	HDB Financial Services Limited CRISIL AAAINE756I08041
9	HDB Financial Services Limited CRISIL AAAINE756I08066
10	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
11	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
12	Bajaj Finance Limited CRISIL AAAINE296A08714
13	Poonawalla Fincorp Limited CRISIL AAAINE511C08AI2
14	HDB Financial Services Limited CRISIL AAAINE756I08058
15	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
16	Tata Capital Housing Finance Limited CRISIL AAAINE033L08163
17	Kotak Investment Advisors Limited CRISIL AAAINE03BW08069
18	Tata Capital Housing Finance Limited CRISIL AAAINE033L08155
19	Tata Sons Private Limited CRISIL AAAINE895D07446
20	Sundaram Finance Limited CRISIL AAAINE660A08BR0

Table 5 WASPAS Debt Rankings (Author's own work)

3.3 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

Introduced in the 1980s, TOPSIS is a multi-criteria decision-making method that selects the alternative with the smallest Euclidean distance from the ideal solution and the largest distance from the negative ideal solution. The positive ideal solution maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Behzadian et al., 2012).

Essentially, it ranks the options by assessing how close each alternative is to the ideal solution.

Step 1) Create a Decision Matrix -

1. Enumerate all alternatives denoted by m and all criteria denoted by n.

2.Create a matrix where each row corresponds to an alternative and each column corresponds to a criterion. The intersection of each alternative and criterion represented as X_{ij}, will form a matrix denoted by $X_{ij}(m*n)$

Step 2) Normalize the Decision Matrix -

Decision matrix is subsequently normalized as different criteria are then converted into scalable units.

$R=(r_{ij})m*n$, by the help of normalised

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \quad (9)$$

Where x_{ij} represents the value of the i^{th} alternative for the j^{th} criterion with i=1, 2....m and j=1, 2.... n.

Step 3) Compute the Weighted Normalized Decision Matrix -

1. Multiply each element in the normalized decision matrix by its corresponding criterion weight.

2. Let w_j be the weight of the j^{th} criterion

3. $v_{ij} = r_{ij}$ x w_j, i=1,2,3.... j=1,2,3....

$$v_{ij} = r_{ij} \times w_j \quad (10)$$

Step 4) Identify the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) -

1. The PIS includes the highest values for each benefit criterion and the lowest values for cost criteria.

$$PIS = \{v_1^+, v_2^+, v_3^+\} \quad (11)$$

2. The NIS comprises the lowest values for each benefit criterion and the highest values for cost criteria.

$$NIS = \{v_1^-, v_2^-, v_3^-\} \quad (12)$$

Step 5) Calculate the Euclidean Distance from the PIS and NIS -

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

1. For each alternative, compute the distance to the PIS (S_i^+) and the NIS (S_i^-) using the Euclidean distance formula

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \quad (13)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (14)$$

Step 6) Calculate the Relative Closeness to the Ideal Solution -

1. Compute the relative closeness of each alternative to the ideal solution

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \quad (15)$$

2. The alternative with the highest C_i^* is considered the best.

Once the final criterion C_i^* is calculated for each company, they are ranked in descending order indicating that a higher value of C_i^* is a better alternative as compared to the others. By the help of the TOPSIS method these are the final top 20 equity stocks and corporate bonds in the below Tables 6-7.

Rank	Name	Industry
1	Bajaj Holdings	Financial Services
2	IDFC Bank	Financial Services
3	Data Infrastructure Trust	Financial Services
4	Vedanta	Metals & Mining
5	Embassy Office Parks REIT	Financial Services
6	Coal India	Oil Gas & Consumable Fuels
7	India Grid Trust	Power
8	Authum Investments	Financial Services
9	Castrol India	Oil Gas & Consumable Fuels
10	IOCL	Oil Gas & Consumable Fuels
11	Colgate-Palmolive	Fast Moving Consumer Goods
12	Nestle India	Fast Moving Consumer Goods
13	Sanofi India	Healthcare
14	ITC	Fast Moving Consumer Goods
15	ICICI Securities	Financial Services
16	Jai Balaji Industries	Power
17	TCS	Information Technology
18	HCL Technologies	Information Technology
19	Nippon Life India AMC	Financial Services
20	Puravankara	Realty

Table 6 TOPSIS Equity Rankings (Author's own work)

Rank	Name
1	NTPC Limited CRISIL AAAINE733E07CB1
2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2
3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
4	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
5	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6
7	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8
8	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8

9	HDB Financial Services Limited CRISIL AAAINE756I08066
10	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
11	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
12	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
13	Poonawalla Fincorp Limited CRISIL AAAINE511C08AI2
14	HDB Financial Services Limited CRISIL AAAINE756I08058
15	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
16	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
17	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
18	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
19	Tata Sons Private Limited CRISIL AAAINE895D07446
20	Sundaram Finance Limited CRISIL AAAINE660A08BR0

Table 7 TOPSIS Debt Rankings (Author's own work)

3.4 Simple Additive Weighting (SAW)

SAW is a prominent and extensively used technique in multi-criteria decision-making. It is employed to address multi-attribute decision problems. This technique allocates weights to each attribute where sum of all weights equals to one. Each alternative is assessed regarding each attribute. The first step of SAW is to calculate r_{ij} by normalizing the value of j^{th} criterion for the i^{th} alternative (Taherdoost & Madanchian, 2023). Where r_{ij} represents the normalized preferred ratings of the i^{th} alternative in relation to the j^{th} criterion, given by

$$r_{ij} = \frac{a_{ij}}{\max_i a_{ij}} \text{ for beneficial,}$$

$$r_{ij} = \frac{\min_i a_{ij}}{a_{ij}} \text{ for non} - \text{beneficial,}$$

For i = 1, 2….m and j = 1, 2…. n.

Next, compute the weighted normalized decision matrix by multiplying each element of the normalized decision matrix by its corresponding weight.

$$V_{ij} = r_{ij} \times w_j \qquad (16)$$

Where w_j represents the weight of the j^{th} criterion, i = 1, 2….m and j = 1, 2…. n.

Then combine the values of the criteria and weights using the following equation

$$P_i = \sum_{j=1}^{n} w_j r_{ij} \qquad (17)$$

Lastly, the alternatives are ranked according to the highest value of P_i and the alternative with the highest value is selected as the best. The top 20 ranked stocks and corporate bonds are presented below in Tables 8-9.

Rank	Name	Industry
1	Bajaj Holdings	Financial Services
2	IDFC Bank	Financial Services
3	Authum Investments	Financial Services
4	Nippon Life India AMC	Financial Services
5	HDFC AMC	Financial Services
6	Tata Investment Corporation	Financial Services
7	Indian Energy Exchange	Financial Services
8	P & G Hygiene	Fast Moving Consumer Goods
9	UTI AMC	Financial Services
10	Embassy Office Parks REIT	Financial Services
11	Sun TV Network	Media Entertainment & Publication
12	CDSL	Financial Services

13	Oracle Financial Services	Information Technology
14	ITC	Fast Moving Consumer Goods
15	Nestle India	Fast Moving Consumer Goods
16	Lloyds Metals	Metals & Mining
17	Colgate-Palmolive	Fast Moving Consumer Goods
18	India Grid Trust	Power
19	HPCL	Oil Gas & Consumable Fuels
20	Jio Financial	Financial Services

Table 8 SAW Equity Rankings (Author's own work)

Rank	Name
1	NTPC Limited CRISIL AAAINE733E07CB1
2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2
3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
4	Poonawalla Fincorp Limited CRISIL AAAINE511C08985
5	Poonawalla Fincorp Limited CRISIL AAAINE511C08AD3
6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6
7	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8
8	HDB Financial Services Limited CRISIL AAAINE756I08041
9	HDB Financial Services Limited CRISIL AAAINE756I08066
10	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
11	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
12	Bajaj Finance Limited CRISIL AAAINE296A08714
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15	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
16	Tata Capital Housing Finance Limited CRISIL AAAINE033L08163
17	Kotak Investment Advisors Limited CRISIL AAAINE03BW08069
18	Tata Capital Housing Finance Limited CRISIL AAAINE033L08155
19	Tata Sons Private Limited CRISIL AAAINE895D07446
20	Sundaram Finance Limited CRISIL AAAINE660A08BR0

Table 9 SAW Debt Rankings (Author's own work)

3.5 Complex Proportional Assessment (COPRAS)

Complex Proportional Assessment (COPRAS) is a Multiple-Criteria Decision-Making (MCDM) method developed in 1996 by scientists Zavadskas and Kaklauskas from Vilnius Gediminas Technical University. This method was detailed in their work, "The New Method of Multicriteria Complex Proportional Assessment Projects, published in the Technological and Economic Development of Economy, Vol 1, No 3, Vilnius: Technika, 1994, pp. 131-139.

In this method, m represents the number of alternatives, n represents the number of criteria being evaluated to determine X_{ij} which shows the performance of the i^{th} alternative with respect to the j^{th} criterion.

The first step is to normalize the data to allow comparison of values which is computed as follows:

$$\overline{X} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}, \ (i = 1 \ldots m, \ j = 1 \ldots n, \ \sum_{j=1}^{n} \overline{X}_{ij} = 1) \qquad (18)$$

This method assumes that the priority and utility of the study alternatives are directly and proportionally related to the system of indices that adequately describes the alternatives, as well as to the values and significance of these indices.

Calculations is shown in the following steps: -

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

Step 1: Calculate the weighted normalised matrix

$d_{ij}= \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \cdot \omega$, (i = 1…m, j=1…n) (19)

Where ω represents the weight of each criterion determined using the entropy method.

Step 2: Calculate the sum of the benefit criteria for each alternative and the sum of cost criteria for each alternative.

$S_{+j} = \sum_{i=1}^{m} d + ij$ (20)

$S_{-j} = \sum_{i=1}^{m} d - ij$ (21)

A greater value of benefit criterion and a lower value of cost criterion is better for each alternative.

Step 3: Calculating the relative significance Q_j of each alternative

$Q_j = S_{+j} + \frac{S_{-min} \cdot \sum_{j=1}^{n} S_{-j}}{S_{-j} \cdot \sum_{j=1}^{n} \frac{S_{-min}}{S_{-j}}}, j = \overline{1, n}$ (22)

Step 4: Determine the priority of alternatives. The higher is Q_j, the higher is the efficiency (priority) of the alternative.

$UD_j = \frac{Qj}{\max (Qj)}$ (23)

Following these steps, the stocks and the corporate bonds were ranked in the descending order of their UD_j value. The top 20 rankings can be seen in Table 10 and Table 11 respectively.

Rank	Name	Industry
1	IDFC Bank	Financial Services
2	Bajaj Holdings	Financial Services
3	Embassy Office Parks REIT	Financial Services
4	GNFC	Chemicals
5	Authum Investments	Financial Services
6	India Grid Trust	Power
7	Coal India	Oil Gas & Consumable Fuels
8	Gujarat State Petronet	Oil Gas & Consumable Fuels
9	Data Infrastructure Trust	Financial Services
10	Vedanta	Metals & Mining
11	General Insurance	Financial Services
12	IOCL	Oil Gas & Consumable Fuels
13	New India Assurance	Financial Services
14	CPCL	Oil Gas & Consumable Fuels
15	ONGC	Oil Gas & Consumable Fuels
16	Colgate-Palmolive	Fast Moving Consumer Goods
17	GE Shipping Co	Services
18	Nestle India	Fast Moving Consumer Goods
19	Nippon Life India AMC	Financial Services
20	Castrol India	Oil Gas & Consumable Fuels

Table 10 COPRAS Equity Rankings (Author's own work)

Rank	Name
1	NTPC Limited CRISIL AAAINE733E07CB1
2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2
3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
4	Poonawalla Fincorp Limited CRISIL AAAINE511C08985
5	Poonawalla Fincorp Limited CRISIL AAAINE511C08AD3
6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6

7	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8
8	HDB Financial Services Limited CRISIL AAAINE756I08041
9	HDB Financial Services Limited CRISIL AAAINE756I08066
10	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
11	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
12	Bajaj Finance Limited CRISIL AAAINE296A08714
13	Poonawalla Fincorp Limited CRISIL AAAINE511C08AI2
14	HDB Financial Services Limited CRISIL AAAINE756I08058
15	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
16	Tata Capital Housing Finance Limited CRISIL AAAINE033L08163
17	Kotak Investment Advisors Limited CRISIL AAAINE03BW08069
18	Tata Capital Housing Finance Limited CRISIL AAAINE033L08155
19	Tata Sons Private Limited CRISIL AAAINE895D07446
20	Sundaram Finance Limited CRISIL AAAINE660A08BR0

Table 11 COPRAS Debt Rankings (Author's own work)

3.6 Preference Ranking Organization Method for Enrichment Evaluations II (PROMETHEE II)

The Preference Ranking Organization Method for Enrichment Evaluations II (PROMETHEE II) is an advanced Multi-Criteria Decision-Making (MCDM) approach that ranks alternatives based on pairwise comparisons across multiple criteria. Unlike PROMETHEE I, PROMETHEE II provides a complete ranking of all alternatives.

Steps to Perform PROMETHEE II:

Step 1: Construct the Decision Matrix and Define Preference Functions

- Create a decision matrix A in which a criterion is represented by a column and an alternative by a row.
- Create a preference function P (a, b) for each criterion to determine how much alternative a is preferred over alternative b.

Step 2: Calculate Preference Indices

- Calculate the preference index π(a,b), for each pair of alternatives (a,b)

$$\pi(a, b) = \sum_{j=1}^{n} wj \cdot Pj(aj, bj) \qquad (24)$$

Where w_j represents the weight of criterion j, and P_j (a_j, bj) represents the preference function for criterion j.

Step 3: Determine Positive and Negative Flows

- For each alternative a, calculate the positive flow $\phi^+(a)$ and the negative flow $\phi^-(a)$:

$$\phi^+(a) = \frac{1}{m-1} \sum_{b \neq a} \pi(a, b) \qquad (25)$$

$$\phi^-(a) = \frac{1}{m-1} \sum_{b \neq a} \pi(b, a) \qquad (26)$$

Where m is the number of alternatives.

Step 4: Calculate the Net Flow

- For each alternative a, compute the net flow ϕ(a):

$$\phi(a) = \phi^+(a) - \phi^-(a) \qquad (27)$$

Step 5: Rank the Alternatives

- Rank the alternatives based on their net flow values ϕ(a). A higher net flow indicates a better alternative.

Following the PROMETHEE II analysis, the stocks and corporate bonds were ranked in descending order based on their net flow values (ϕ). The top 20 rankings are presented in Table 12 and Table 13, respectively.

Rank	Company Name	Industry
1	Embassy Office Parks REIT	Financial Services
2	India Grid Trust	Power
3	Authum Investments	Financial Services
4	Data Infrastructure Trust	Financial Services
5	Vedanta	Metals & Mining
6	Bajaj Holdings	Financial Services
7	Power Grid Corporation	Power
8	L&T Finance Ltd	Financial Services
9	Nippon Life India AMC	Financial Services
10	Coal India	Oil Gas & Consumable Fuels
11	ICICI Securities	Financial Services
12	HDFC AMC	Financial Services
13	REC Ltd	Financial Services
14	UTI AMC	Financial Services
15	Sun TV Network	Media Entertainment & Publication
16	ITC	Fast Moving Consumer Goods
17	Castrol India	Oil Gas & Consumable Fuels
18	GE Shipping Co	Services
19	Puravankara Ltd.	Realty
20	Aditya AMC	Financial Services

Table 12 PROMETHEE Equity Rankings (Author's own work)

Rank	Corporate Bond
1	NTPC Limited CRISIL AAAINE733E07CB1
2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2
3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
4	Poonawalla Fincorp Limited CRISIL AAAINE511C08985
5	Poonawalla Fincorp Limited CRISIL AAAINE511C08AD3
6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6
7	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8
8	HDB Financial Services Limited CRISIL AAAINE756I08041
9	HDB Financial Services Limited CRISIL AAAINE756I08066
10	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
11	Tata Capital Financial Services Limited CRISIL AAAINE306N080291
12	Bajaj Finance Limited CRISIL AAAINE296A08714
13	Poonawalla Fincorp Limited CRISIL AAAINE511C08AI2
14	HDB Financial Services Limited CRISIL AAAINE756I08058
15	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
16	Tata Capital Housing Finance Limited CRISIL AAAINE033L08163
17	Kotak Investment Advisors Limited CRISIL AAAINE03BW08069
18	Tata Capital Housing Finance Limited CRISIL AAAINE033L08155

19	Tata Sons Private Limited CRISIL AAAINE895D07446
20	Sundaram Finance Limited CRISIL AAAINE660A08BR0

Table 13 PROMETHEE Debt Rankings (Author's own work)

3.7 Efficiency Frontier from Modern Portfolio Theory

An Efficient Frontier represents a collection of investment portfolios that are anticipated to offer the highest returns for a given level of risk, or alternatively, to minimize risk for a given level of return. A portfolio is said to be efficient if there is no other portfolio that offers higher returns for a lower or equal amount of risk (Benchener & Li, 2021). The efficiency frontier forms a curved line that illustrates the relationship between risks and returns for a portfolio. It is depicted by plotting the expected returns on the y-axis and the standard deviation (risk) of the portfolio on the x-axis.

The daily spot prices of each commodity were collected and utilised to compute daily returns and the standard deviation to quantify daily risk. Once this data is collected a covariance matrix is created that shows pairwise correlations between assets within a portfolio as shown in Table 14.

Covariance	Gold	Silver	Copper	Aluminium
Gold	0.00004750080	0.00006980238	0.00000951826	0.00000794526
Silver	0.00006980238	0.00017752371	0.00003467947	0.00002505052
Copper	0.00000951826	0.00003467947	0.00013096164	0.00002424082
Aluminium	0.00000794526	0.00002505052	0.00002424082	0.00012823381

Table 14 Commodity Covariance Matrix (Author's own work)

Once this matrix is created, different weights are assigned to each commodity to understand the portfolio's return and risk. A modified Sharpe ratio is also calculated to better compare commodities as returns and risk are both used in the formula for it. Using the various weights, 10,000 simulations were run in Excel to find the best combination of maximum return and minimal risk. The results of these simulations are plotted on a chart to create the efficiency frontier curved line as shown per Figure 1.

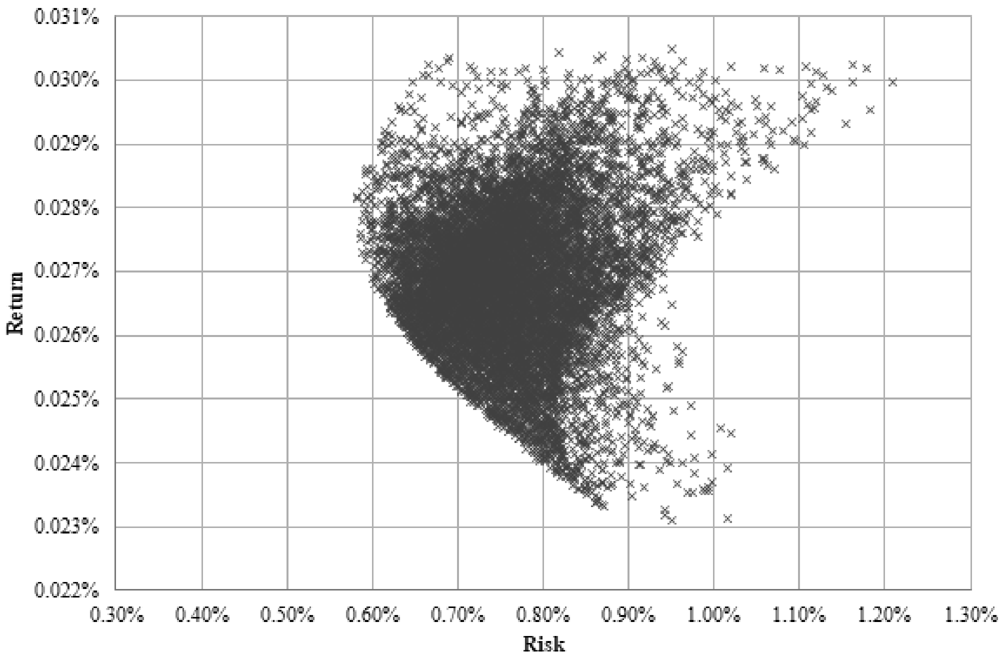

Figure 1 Commodity Efficiency Frontier (Author's own work)

From the chart the ideal point is selected and calculated using Solver in Excel to determine the maximum value of the modified sharpe ratio which is calculated by dividing the expected returns with standard deviation. Solver optimized the modified sharpe ratio by adjusting the weights assigned to the 4 different commodities, aiming to maximize Sharpe ratio. The results depicting the various weights for each commodity alongside the portfolio expected return, standard deviation and modified sharpe ratio are presented in Table 15 below.

	Gold	Silver	Copper	Aluminium
Expected Return	0.030725%	0.030429%	0.023702%	0.022736%
Standard Deviation	0.689142%	1.332253%	1.144275%	1.132295%
Weights Allocated	0.721342	0	0.137614	0.141043
Portfolio Expected Return	0.028631%			
Portfolio Standard Deviation	0.584764%			
Modified Sharpe	4.896231			

Table 15 Efficiency Frontier Results (Author's own work)

3.8 Mean Rank

The mean rank method is a straightforward aggregation approach where each alternative is assessed and ranked based on each criterion. The mean rank for each alternative is then calculated by averaging its ranks across all criteria. The alternative with the lowest mean rank is considered the best. (Jing et al., 2023)

$$\text{Mean Rank}_{i} = \frac{1}{n}\sum_{j=1}^{n} Rij \qquad (28)$$

Where R_{ij} represents the rank of the i^{th} alternative under the j^{th} criterion and n represents the total number of criteria.

3.9 Borda Count

The Borda count is a voting method that ranks alternatives based on various or multiple criteria. Each criterion assigns ranks to all alternatives, with higher ranks indicating better performance. The Borda count aggregates these ranks by assigning points corresponding to their positions; for example, in a set of m alternatives, the top-ranked alternative receives m−1 points, the second-ranked alternative receives m−2 points, and so on. The points from all criteria are summed for each alternative, and the alternative with the highest total score is considered the best. (Jing et al., 2023) The Borda count method accounts for the collective preferences across all criteria and is especially useful in ensuring that consistently high-performing alternatives are ranked higher.

$$\text{Borda Score}_{I} = \sum_{j=1}^{n}\left(m - R_{ij}\right) \qquad (29)$$

Where R_{ij} represents the rank of the i^{th} alternative under the j^{th} criterion, m represents the total number of alternatives and n represents the total number of criteria.

4. CONCLUSION

To better understand which ratios, affect the attractiveness of stocks Entropy was run on 493 stocks and the results show return on equity (ROE) to have the highest importance with operating profit margins (OPM) following close. Both are profitability ratios and ROE depicts how well the company makes profits from equity. Shareholders occupy the lowest rank in a pecking order of company's capital structure, and the returns they receive serve as an important indicator of the surplus profits left after fulfilling required payment obligations and reinvesting in the business.

The same weighting method Entropy was used for the corporate bonds to measure the importance of credit ratings and interest rates. Credit rating was given the highest importance with 96% signifying that to be the determining factor to be considered while choosing a bond. Credit ratings are determined by evaluating a borrower's financial resources, including money, assets, and existing debt, as well as their track record of repaying previous debts. Thus, for investors a higher credit rating shows them that their investments are safe, and the companies are reliable.

After obtaining rankings from different MCDM methods, we have found a cumulative rank of the stocks and corporate bonds with the help of Borda and Mean Ranking. Given below is a table showing a list of the top 20 ranked stocks and corporate bonds obtained from this hybrid MCDM model.

Rank	Mean Rank	Borda Count
1	Bajaj Holdings	Bajaj Holdings
2	Authum Investments	Authum Investments
3	Embassy Office Parks REIT	Embassy Office Parks REIT
4	Nippon Life India AMC	Nippon Life India AMC
5	India Grid Trust	India Grid Trust
6	IDFC Banke	IDFC Banke

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

7	ITC	ITC
8	UTI AMC	UTI AMC
9	Coal India	Coal India
10	Colgate-Palmolive	Colgate-Palmolive
11	I O C L	I O C L
12	HDFC AMC	HDFC AMC
13	Sun TV Network	Sun TV Network
14	Oracle Financial Services	Oracle Financial Services
15	Sanofi India	Sanofi India
16	Castrol India	Castrol India
17	Aditya AMC	Aditya AMC
18	GE Shipping Co	GE Shipping Co
19	L&T Finance Ltd	L&T Finance Ltd
20	Glenmark Life	Glenmark Life

Table 16 Final Equity Rankings (Author's own work)

Rank	Mean Rank	Borda
1	NTPC Limited CRISIL AAAINE733E07CB1	NTPC Limited CRISIL AAAINE733E07CB1
2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2	Kotak Mahindra Prime Limited CRISIL AAAINE916D08DT2
3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1	Poonawalla Fincorp Limited CRISIL AAAINE511C08AE1
4	Poonawalla Fincorp Limited CRISIL AAAINE511C08985	Poonawalla Fincorp Limited CRISIL AAAINE511C08985
5	Poonawalla Fincorp Limited CRISIL AAAINE511C08AD3	Poonawalla Fincorp Limited CRISIL AAAINE511C08AD3
6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AG6
7	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8	Poonawalla Fincorp Limited CRISIL AAAINE511C08AK8
8	HDB Financial Services Limited CRISIL AAAINE756I08041	HDB Financial Services Limited CRISIL AAAINE756I08041
9	HDB Financial Services Limited CRISIL AAAINE756I08066	HDB Financial Services Limited CRISIL AAAINE756I08066
10	Tata Capital Financial Services Limited CRISIL AAAINE306N08029	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
11	Tata Capital Financial Services Limited CRISIL AAAINE306N08029	Tata Capital Financial Services Limited CRISIL AAAINE306N08029
12	Bajaj Finance Limited CRISIL AAAINE296A08714	Bajaj Finance Limited CRISIL AAAINE296A08714
13	Poonawalla Fincorp Limited CRISIL AAAINE511C08AI2	Poonawalla Fincorp Limited CRISIL AAAINE511C08AI2
14	HDB Financial Services Limited CRISIL AAAINE756I08058	HDB Financial Services Limited CRISIL AAAINE756I08058
15	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6	Poonawalla Fincorp Limited CRISIL AAAINE511C08AL6
16	Tata Capital Housing Finance Limited CRISIL AAAINE033L08163	Tata Capital Housing Finance Limited CRISIL AAAINE033L08163
17	Kotak Investment Advisors Limited CRISIL AAAINE03BW08069	Kotak Investment Advisors Limited CRISIL AAAINE03BW08069
18	Tata Capital Housing Finance Limited CRISIL AAAINE033L08155	Tata Capital Housing Finance Limited CRISIL AAAINE033L08155

19	Tata Sons Private Limited CRISIL AAAINE895D07446	Tata Sons Private Limited CRISIL AAAINE895D07446
20	Sundaram Finance Limited CRISIL AAAINE660A08BR0	Sundaram Finance Limited CRISIL AAAINE660A08BR0

Table 17 Final Debt Rankings (Author's own work)

Both methods provide exact same results for the top 20 stocks and stay similar for the rest of the dataset as well. As depicted by the results in Table 16 companies in the financial services, oil gas & consumable fuels and information technology sectors have been assigned the highest ranks by the hybrid MCDM model. The Financial Services industry not only forms a major part of Nifty 500 (around 20%) but also have dominated the top 20 rankings for equity. A possible reason for this might be the increased accessibility to financial services through digitization following COVID-19 in India.

The results of the efficiency frontier signify the importance of Gold over the other commodities. The table shows Gold to have highest expected returns with the lowest standard deviation making it the best suitable option for the portfolio. Furthermore, Copper and Aluminium have a lower standard deviation than Silver making them safer investments. A diversified portfolio also tends to be less risky and as seen by the Covariance Matrix the correlation between Gold and Copper or Aluminium is lower than for Silver. Hence, the efficiency frontier has created an optimum portfolio comprising of these commodities.

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