ISSN 2277-2685
IJESR/Jan-Mar. 2025/ Vol-15/Issue-1/615-623
Dr.K.Sujatha *et. al.,* / International Journal of Engineering & Science Research

Application of Fuzzy Analytic Hierarchy Process to Assess Key Financial Indicators Influencing Indian Stock Market Investments

[1]Dr.K.Sujatha

[1]Associate Professor,Department of Mathematics,Tara Government College (A),Sangareddy,Telangana ,India ,502001

[1]E- mail id: sujatha.kudum@gmail.com

Abstract

This research examines the principal financial factors affecting investment decision-making in the Indian stock market through the application of the Fuzzy Analytic Hierarchy Process (FAHP). Financial data were obtained from the top ten companies listed on the Bombay Stock Exchange (BSE), while expert evaluations were gathered from two senior specialists—an experienced investor and a finance professor—each possessing more than fifty years of professional expertise. The analysis focused on four key financial criteria: Return on Equity (ROE) (C1), Earnings Per Share (EPS) (C2), Price-to-Earnings (P/E) ratio (C3), and Debt-to-Equity (D/E) ratio (C4). The FAHP results indicate that Return on Equity (ROE) (C1) is the most influential criterion in investment decision-making. The findings further reveal that indicators related to profitability carry greater weight in investor preferences, while liquidity-related measures have comparatively limited impact. Overall, the study offers valuable insights for investors by underscoring the importance of prioritizing profitability and growth-oriented metrics over short-term solvency considerations when constructing investment portfolios.

Keywords

Fuzzy Analytic Hierarchy Process (FAHP); Investment Decision-Making; Indian Stock Market; Financial Performance Indicators; Return on Equity; Multi-Criteria Decision Making (MCDM).

1. Introduction

An active and well-functioning capital market is widely recognized as a hallmark of economic development at both national and international levels. Vibrant markets not only enhance financial integration but also facilitate capital formation, which in turn contributes to the growth and prosperity of industries across sectors. Investor participation plays a crucial role in this process, as their willingness to take an active role in trading fosters liquidity, efficiency, and market stability. To maximize returns, investors generally prefer to select stocks of companies that demonstrate strong financial performance and upward stock price trends. However, because financial markets are inherently uncertain, investors face challenges in predicting future returns with certainty.

Consequently, portfolio diversification becomes an essential strategy to minimize the risk of losses while ensuring sustainable growth (Secme et al., 2009). Portfolio selection has long been regarded as a central issue in finance, as it represents a classic case of decision-making under risk. Since the future returns of assets are not known at the time of investment, investors must rely on ex-ante models to guide their decisions. The performance of such decisions can only be evaluated once the uncertainty surrounding asset returns is resolved. Thus, portfolio selection models serve as critical decision-making tools, enabling investors to evaluate trade-offs between risk and return in advance (Roman & Mitra, 2009). The foundation of modern portfolio theory (MPT) was laid by Markowitz (1952), who introduced the mean-variance framework. In this approach, portfolio risk is measured by the variance and covariance of asset returns, leading to a quadratic programming formulation for constructing efficient portfolios. The Markowitz model was later extended by Sharpe (1966), Lintner (1965), and Mossin (1966), which collectively gave rise to the Capital Asset Pricing Model (CAPM). These developments firmly established the mean-variance approach as a cornerstone of portfolio management, guiding investors and fund managers in their pursuit of efficient portfolios that maximize diversification benefits. Despite its popularity, traditional portfolio selection models face limitations when applied to real-world scenarios. Investors often consider multiple qualitative and quantitative factors—such as firm size, financial ratios, stock market conditions, and managerial performance—when evaluating stocks. These factors are often conflicting, interdependent, and subject to uncertainty. The task of identifying, comparing, and weighting such criteria in stock selection is both complex and computationally demanding. To address this challenge, researchers have increasingly turned to multi-criteria decision-making (MCDM) methods, which enable systematic evaluation of alternatives under multiple attributes. In particular, the integration of fuzzy logic into MCDM provides a powerful framework for handling uncertainty, vagueness, and imprecision in financial decision-making. A hybrid fuzzy decision-making approach, therefore, offers a robust methodology for portfolio selection by combining quantitative rigor with qualitative judgment, ultimately assisting investors in constructing optimal portfolios under uncertainty.

1.1.Literature Review

Since its inception, the fuzzy Analytic Hierarchy Process (FAHP) has become one of the most widely adopted fuzzy multi-criteria decision-making (MCDM) methods, addressing the limitations of Saaty's crisp AHP in handling vagueness and uncertainty in expert judgments. Early contributions, such as Chang's (1996) extent analysis method based on triangular fuzzy numbers, provided the foundation for practical FAHP applications that could convert subjective preferences into decision weights. During the following decades, FAHP gained increasing attention across diverse domains, with Kahraman (2008) presenting comprehensive theoretical advancements and applications in engineering, management, and finance. At the same time, methodological critiques, such as those of Wang and Chin (2008), highlighted issues with the robustness of fuzzy pairwise comparison matrices, encouraging refinements in weighting procedures and consistency checks.

In the financial domain, FAHP began to gain traction in the late 2000s. Tiryaki and Ahlatcıoğlu (2009) demonstrated one of the first FAHP-based portfolio selection models, showing its potential to incorporate investor preferences and qualitative judgments into asset ranking. Similarly, Roman and Mitra (2009) emphasized the importance of multi-criteria approaches in portfolio selection under uncertainty, reinforcing FAHP's relevance for financial decision-making. Building on this foundation, subsequent research explored hybrid models, where FAHP was combined with other MCDM techniques such as TOPSIS, GRA, and VIKOR. These hybrid frameworks allowed FAHP to generate criteria weights, followed by ranking alternatives using distance- or relation-based methods. Such combinations proved especially effective in evaluating stocks and mutual funds, where both quantitative ratios and qualitative indicators must be integrated (Paul et al., 2021; Senfi, 2024).

At the same time, extensions of FAHP into richer fuzzy set environments further expanded its methodological capabilities. Intuitionistic FAHP (Yu et al., 2021), fuzzy ANP (Rahiminezhad Galankashi et al., 2020), and more recent innovations such as Pythagorean (Milošević, 2023; Başaran, 2023), spherical (Mathew, 2020), and Fermatean fuzzy AHP approaches have enhanced the flexibility of decision models, offering better representation of uncertainty and hesitation in expert judgments. Comprehensive bibliometric analyses, such as Castelló-Sirvent et al. (2022), confirm that FAHP-related publications have grown exponentially, diversifying into finance, sustainability, and supply chain management. Beyond FAHP, other fuzzy MCDM frameworks also support financial decision-making. Liu et al. (2012) developed a fuzzy portfolio selection model incorporating return, transaction cost, risk, and skewness, simulating real-world transactions to provide investors with robust alternatives. Shamsuzzaman et al. (2013) applied fuzzy MCDM in an industrial context by ranking coals based on calorific value and chemical composition, while Gupta et al. (2013) introduced a hybrid portfolio optimization model integrating both financial and ethical criteria using AHP and fuzzy MCDM. These studies collectively emphasize the value of fuzzy-based frameworks in addressing complex, uncertain, and multi-dimensional decision problems, while also recognizing the role of structured expert consensus methods, such as Delphi, to enhance judgment reliability.

Despite its contributions, this study has certain limitations. First, the analysis is based on a limited sample of ten companies listed on the Bombay Stock Exchange, which may restrict the generalizability of the findings across the broader Indian stock market. Second, expert judgments were obtained from only two professionals, and although they possess extensive experience, incorporating a larger and more diverse panel of experts could enhance the robustness of the results. Third, the study considers a restricted set of financial criteria and does not account for macroeconomic factors, market sentiment, or industry-specific risks that may influence investment decisions. Future research may address these limitations by expanding the sample size, including additional financial and non-financial criteria, and integrating FAHP with other advanced decision-making or forecasting models.

2.1. Fuzzy Analytic Hierarchy Process (Fuzzy AHP)

The Analytic Hierarchy Process (AHP), introduced by Thomas L. Saaty in 1980, simplifies complex decision-making by structuring it into a hierarchical model and employing pairwise comparisons to establish priority scales. To address the uncertainty in judgments, this method has been enhanced with Triangular Fuzzy Numbers (TFNs), allowing for a more flexible and nuanced evaluation.

1. Developing a fuzzy comparison matrix

First the scale of linguistics is determined. The scale used is the TFN scale from one to nine are shows in Table 1.

Table 1. Scale of Interest

Scale of Interest	Linguistic Variable	Membership Function
1	Equally important	(1,1,1)
3	Weakly important	(2,3,4)
5	Strongly more important	(4,5,6)
7	Very strongly important	(6,7,8)
9	Extremely important	(8,9,10)

Then, using the TFN to make pair-wise comparison matrix for the main criteria and sub-criteria. Equation (1) shows the form of fuzzy comparison matrix.

$$\bar{\mathcal{A}} = \begin{bmatrix} 1 & \cdots & \overline{a_{1n}} \\ \vdots & \ddots & \vdots \\ \overline{a_{n1}} & \cdots & 1 \end{bmatrix} \tag{1}$$

2. Define Fuzzy Geometric Mean

The fuzzy geometric mean is then calculated using Equation (2)[13]:

$$\bar{x_\iota} = \left(\bar{a}_{(i1)} \otimes \bar{a}_{(i2)} \otimes \ldots \otimes \bar{a}_{(in)}\right)^{\frac{1}{n}} \tag{2}$$

Where $\tilde{a}_{in}$ is a value of fuzzy comparison matrix from criteria I to n. Result from the fuzzy geometric mean will be referred to later as local fuzzy number.

3. Calculate the weight of fuzzy of each dimension

The next step is to calculate the global fuzzy number for each evaluation dimension with Equation (3).

$$\widetilde{w}_i = \tilde{x}_1 \otimes (\tilde{x}_1 \oplus \tilde{x}_1 \oplus \dots \oplus \tilde{x}_1)^{-1} \quad (3)$$

4. Define the best non fuzzy performance (BNP)

The global fuzzy number is then converted to crisp weight value using the Centre of Area (COA) method to find the value of best BNP from the fuzzy weight in each dimension, calculated using Equation (4).

$$BNP_{wi} = \frac{[(u_{wi} - l_{wi}) + (m_{wi} - l_{wi})]}{3} + l_{wi} \quad (4)$$

2.2. Case study

In this study, data were collected from the top 10 companies listed on the Bombay Stock Exchange (BSE), India (https://www.bseindia.com/). Expert opinions were obtained from two professionals: (i) an experienced investor and (ii) a professor of finance. Both experts possess more than 50 years of experience in the field of investments, ensuring credibility in the evaluation process. The study considered six key financial criteria:C1 – Return on Equity (ROE), C2 – Earnings Per Share (EPS), C3 – Price-to-Earnings (P/E) Ratio, C4 – Debt-to-Equity (D/E) Ratio, The Fuzzy Analytic Hierarchy Process (FAHP) was then employed to determine the relative importance weights of these criteria, with the results presented in Table 1

Table 1: Determining the weights of the criteria by FAHP Approach

Criteria	C_1	C_2	C_3	C_4
Fuzzy Weights	0.2502	0.2048	0.2190	0.1701
Rank	1	2	3	4

2.3. Results and Discussion

The dominance of Return on Equity (ROE) as the most influential factor aligns with the general investor focus on profitability, which is crucial for long-term growth potential. Profitability metrics, such as ROE and EPS, offer clear insights into the company's ability to generate returns relative to its equity base and earnings. These are key indicators of financial health and are often prioritized by investors looking for high-growth opportunities. The relatively low significance of liquidity indicators like the Debt-to-Equity ratio (D/E) suggests that investors in this market are less concerned with a company's immediate solvency. This may reflect a broader market context where growth-oriented metrics are more likely to drive returns, even at the cost of higher leverage. Additionally, the P/E ratio serves as a secondary indicator, providing insight into market expectations of future earnings growth, but it remains secondary to direct profitability measures. The findings underscore the need for investors to place greater emphasis on profitability and growth metrics when constructing portfolios in the Indian stock market, as opposed to focusing on short-term liquidity and solvency indicators. This may also guide investment strategies tailored to market conditions that favor companies with strong earnings potential

3. Conclusion

This study applied the Fuzzy Analytic Hierarchy Process (FAHP) to evaluate and prioritize key financial criteria influencing investment decisions in the Indian stock market. By analyzing data from leading companies listed on the Bombay Stock Exchange and incorporating expert judgments, the study effectively addressed the uncertainty and subjectivity inherent in financial decision-making. The results identified Return on Equity (ROE) as the most significant criterion, highlighting the dominant role of profitability measures in guiding investor preferences. Earnings Per Share and valuation indicators also contributed to decision-making, while leverage-related measures exhibited relatively lower importance. These findings suggest that investors place greater emphasis on long-term profitability and growth potential rather than short-term financial structure considerations. The FAHP-based framework presented in this study provides a structured and reliable decision-support tool that can assist investors in making informed portfolio selection decisions under uncertainty.

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