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RESEARCH ARTICLE

An Application On Evaluation Of Fund Selection Criteria In The Individual Retirement System (IRS) With Multi-Criteria Decision-Making Methods

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Abstract

Investing involves allocating current financial resources with the expectation of generating future returns. The primary goal of investing is to grow wealth, ensure financial security, and achieve specific financial objectives such as retirement savings. There are various types of investments, including stocks, bonds, mutual funds, and real estate, each with a risk and return profile. Effective investment strategies often involve diversification to mitigate risk and maximize returns. Within retirement planning, the Individual Retirement System (IRS) plays a crucial role. The IRS allows individuals to contribute a portion of their income into retirement accounts, which are then invested in various financial instruments. This system provides a structured approach to retirement savings, offering flexibility and significant tax advantages. The selection of appropriate funds within these accounts is vital to ensuring optimal growth and security of retirement savings. This study aims to evaluate the criteria affecting fund selection in BES using two important multi-criteria decision-making methods: Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP). By applying AHP and ANP, the study defines the effects of basic factors such as risk tolerance, liquidity, fund performance, and diversification on fund selection in BES and evaluates their impact levels. The study aims to increase investment decisions' soundness and reliability and help individuals make informed choices compatible with their financial goals and risk preferences. At the end of the study, the impact levels of the criteria affecting fund selection were calculated, and the results were interpreted.
Keywords: *Multi-Criteria Decision-Making, Fund Selection, Individual Retirement System, AHP, ANP*
Jel Codes: *C44, M10, M12*

Çok Kriterli Karar Verme Yöntemleri İle Bireysel Emeklilik Sisteminde (BES) Fon Seçim Kriterlerinin Değerlendirilmesi Üzerine Bir Uygulama

Özet

Yatırım, mevcut finansal kaynakların gelecekte getiri elde etme beklentisiyle tahsis edilmesini anlamına gelir. Yatırımın temel amacı serveti artırmak, finansal güvenliği sağlamak ve emeklilik tasarrufları gibi belirli finansal hedeflere ulaşmaktır. Hisse senetleri, tahviller, yatırım fonları ve gayrimenkul dahil olmak üzere her birinin kendi risk ve getiri profili olan çeşitli yatırım türleri vardır. Etkili yatırım stratejileri genellikle riski azaltmak ve getirileri en üst düzeye çıkarmak için çeşitlendirmeyi içerir. Emeklilik planlaması alanında Bireysel Emeklilik Sistemi (BES) önemli bir rol oynamaktadır. BES, bireylerin gelirlerinin bir kısmını emeklilik hesaplarına yatırmalarına ve daha sonra bu hesapları çeşitli finansal araçlara yatırmalarına olanak tanır. Bu sistem emeklilik tasarruflarına yapısal bir yaklaşım sunarak esneklik ve önemli vergi avantajları sunar. Bu hesaplardaki uygun fonların seçimi, optimal büyümenin ve emeklilik tasarruflarının güvenliğinin sağlanması açısından hayati öneme sahiptir. Bu çalışma, BES'de fon seçimini etkileyen kriterleri iki önemli çok kriterli karar verme yöntemini kullanarak değerlendirmeyi amaçlamaktadır: Analitik Hiyerarşi Süreci (AHP) ve Analitik Ağ Süreci (ANP). Çalışmada, AHP ve ANP'yi uygulayarak, BES'de fon seçimini etkileyen risk toleransı, fon performansı, likidite ve çeşitlilik gibi temel faktörlerin fon seçimi üzerindeki etkileri tanımlamakta ve etki düzeyleri değerlendirmektedir. Çalışmada amaç ise, yatırım kararlarının sağlamlığını ve güvenilirliğini artırmak, bireylerin finansal hedefleri ve risk tercihleriyle uyumlu bilinçli seçimler yapmalarına yardımcı olmaktır. Çalışma sonunda fon seçimini etkileyen kriterlerin etki düzeyleri hesaplanmış ve sonuçlar yorumlanmıştır.
Anahtar kelimeler: *Çok Kriterli Karar Verme, Fon Seçimi, Bireysel Emeklilik Sistemi, AHP, ANP*
Jel Kodu: *C44, M10, M12*

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1. INTRODUCTION

Investing involves the allocation of current income with the expectation of future financial returns. The primary goal of investment is to enhance financial security, preserve and grow wealth, save for retirement, or achieve specific financial objectives. There are various types of investments, including stocks, bonds, mutual funds, real estate, and more. Each investment type carries its own risk and return profile, requiring investors to balance their portfolios according to their risk tolerance and financial goals. Effective investment strategies often involve diversification to mitigate risk and maximize potential returns. This careful planning and strategy are crucial in navigating the complex financial markets and achieving long-term financial success (Pinto, 2012).

The Individual Retirement System (IRS) plays a critical role in retirement planning. The IRS allows individuals to contribute a portion of their income into a retirement account, which is then invested in various financial instruments. This system is designed to provide financial security in retirement by ensuring that individuals have sufficient funds to support themselves after they stop working. The flexibility of the IRS allows for a wide range of investment choices, enabling participants to customize their retirement savings strategy according to their financial goals and risk appetite. This system not only encourages personal savings but also provides significant tax advantages, making it a crucial component of a comprehensive retirement plan (Kantarcı and Soest, 2013).

Multi-criteria decision-making (MCDM) is a valuable approach in the context of the IRS. MCDM methods, such as the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP), help individuals and financial planners evaluate various investment options and strategies based on multiple criteria. These criteria can include risk, return, liquidity, and tax implications. By systematically comparing these factors, MCDM provides a structured framework for making informed and rational investment decisions. This approach is particularly useful in the dynamic and uncertain environment of financial markets, where numerous variables must be considered to optimize investment outcomes (Coetzee, 2013).

In this study, both AHP and ANP will be utilized to evaluate criteria that are used to decide fund alternatives in the IRS. By applying these methods, we aim to provide a detailed analysis of various fund options, considering multiple criteria and their interrelationships. The advantages of using AHP and ANP in this context include their ability to handle both qualitative and quantitative data, accommodate complex decision structures, and enhance the robustness and reliability of investment decisions. This comprehensive approach will aid individuals in making informed choices that align with their long-term financial goals and risk preferences, ultimately improving the effectiveness of their retirement planning.

The remainder of the study is organized as follows. In the second part, comprehensive information about the IRS system is given. In the third section, literature information about the methods used in fund selection is given. In addition, the areas in which the methods used in the study have been used before are also explained under subheadings. In the next section, the methods used in the study are explained. In the next section, the implementation steps are explained step by step. In the last section, the findings obtained from the study are interpreted.

2. INDIVIDUAL RETIREMENT SYSTEM (IRS)

IRS is designed to provide individuals with a structured means of saving for retirement, independent of employer-sponsored pension plans. These systems allow individuals to contribute a portion of their income to a retirement account, which grows over time through investments in various financial products such as stocks, bonds, and mutual funds. The primary advantage of the IRS is the flexibility it offers; individuals can tailor their retirement savings strategy to fit their personal financial goals and risk tolerance. Unlike traditional pension plans, which promise a defined benefit upon retirement, individual retirement accounts typically operate on a defined contribution basis, where the retirement benefit depends on the amount contributed and the performance of the chosen investments. This shift from defined benefit to defined contribution places more responsibility on individuals to manage their retirement savings effectively (Consigli et al., 2012; Gale and John, 2018).

One of the critical aspects of an IRS is the variety of investment options available. Participants can choose from a wide range of investment vehicles, including conservative options like bonds and more aggressive growth options like stocks. This diversity allows for the customization of portfolios to match the individual's age, retirement timeline, and risk appetite. For younger investors, a portfolio heavily weighted towards equities might be suitable due to the long investment horizon and the potential for higher returns. Conversely, individuals nearing retirement may prefer a more conservative mix to preserve capital. The flexibility of investment choices within the IRS is a significant advantage, as it can help mitigate the risks associated with market volatility and economic downturns (Olson and Phillips, 2015).

Tax advantages are another pivotal feature of Individual Retirement Systems. Contributions to certain types of retirement accounts, like traditional IRAs, are often tax-deductible, which can reduce an individual’s taxable income for the year of the contribution. Additionally, the investment growth within these accounts is typically tax-deferred, meaning that taxes on gains, dividends, and interest are not paid until the funds are withdrawn, usually during retirement. This tax deferral can result in significant tax savings over the long term, as the compounding returns are not diminished by annual taxes. In contrast, Roth IRAs offer tax-free growth and tax-free withdrawals in retirement, provided certain conditions are met, which can be advantageous for those who expect to be in a higher tax bracket in the future. The choice between traditional and Roth accounts depends on the individual's current and expected future tax situation (Wilton, 1974).

Despite the benefits, the IRS also comes with challenges. One major challenge is the risk management burden placed on individuals. Unlike traditional pension plans managed by professional fund managers, individuals in an IRS must make their own investment decisions, which can be daunting for those without financial expertise. Poor investment choices can significantly impact retirement outcomes. Additionally, there is the risk of outliving one’s savings, particularly if the individual withdraws funds too quickly or if the investments perform poorly. To mitigate these risks, it is often recommended that individuals seek professional financial advice and consider annuity products that provide a guaranteed income stream for life (Bingley et al., 2001).

IRS offers a valuable means for individuals to save for retirement independently. They provide flexibility in investment choices, potential tax advantages, and the ability to tailor a retirement savings plan to personal needs. However, they also require individuals to take on significant responsibility for managing their investments and planning for longevity. As such, education and professional advice are crucial components of a successful retirement strategy. By understanding and leveraging the benefits and addressing the challenges, individuals can effectively use the IRS to secure their financial future (Şahin and Başarır, 2019).

3. LITERATURE REVIEW

In this part of the study, a comprehensive literature review was conducted. First, studies on fund selection were scanned. Afterward, it is mentioned in which areas the methods used in the study have been used before.

3.1. Fund Selection

Investment strategies often leverage MCDM methods to optimize fund selection, ensuring balanced risk and return profiles. A study by Palanisamy and Selvam (2011) explored the stock selection abilities of Indian mutual fund managers using conditional models, demonstrating that effective stock selection can significantly enhance fund performance. Building on this, Fiala and Borovička (2015) proposed a two-step MCDM procedure combining fuzzy ELECTRE I and interactive multiple-objective programming, which helps in making investment decisions under uncertainty. In a related study, de Roon et al. (2010) analyzed the factors influencing fund of funds managers' decisions to include single-strategy hedge funds, emphasizing the importance of ex-post alpha, tracking error, and manager characteristics in the selection process.

Budiono and Martens (2010) further highlighted the significance of incorporating fund characteristics alongside past performance to achieve superior fund selection results, significantly increasing yearly alpha and excess net returns. Ferreira et al. (2009) introduced a decision model for portfolio selection based on Decision Theory and Bayesian Analysis, applied to Brazilian financial market data, underscoring the need for systematic approaches in investment strategies. Additionally, a 2023 study utilized the TOPSIS method to evaluate investment options based on critical criteria such as Return on Investment, Risk, and Liquidity, demonstrating the practical applications of MCDM in investment decisions.

Saraoglu and Detzler (2002) discussed a sensible mutual fund selection model using AHP, providing a flexible approach for generating asset allocation recommendations and identifying suitable funds within an asset class. Moreover, Abdel-Azim et al. (2023) developed a Neutrosophic Decision Making Model to address the challenges investors face due to uncertain data and multiple influencing factors in fund selection. Wei et al. (2008) presented a nonlinear and dynamic model based on the return variance model to optimize fund portfolio gain, emphasizing the evolving nature of investment decision-making methodologies. Collectively, these studies illustrate the diverse applications and advantages of MCDM methods in enhancing investment strategies and fund selection processes. Narayanamoorthy & Aravanan (2003) explore the use of the Multiplier Approach for investment decisions in ten companies from five different sectors. It highlights how this method serves as a comprehensive tool to assess and guide investments based on sector-specific metrics. Fiala & Borovička (2015) propose a fuzzy ELECTRE I approach coupled with interactive multiple objective programming to assist investment decisions under uncertainty. The two-step procedure helps investors evaluate potential investments across diverse criteria, ensuring robust decision-making in complex environments. Sánchez et al. (2000) apply the Analytic Hierarchy Process (AHP) to assess investment alternatives in open capital organizations. The AHP method enables investors to systematically evaluate options from different economic sectors, considering various financial and non-financial criteria.

3.2. AHP Literature

The AHP has been widely applied in various decision-making contexts over the past five years. For instance, Romadona (2019) utilized AHP to aid in selecting the best school principal in North Labuhan Batu Regency, demonstrating its effectiveness in educational settings. Kuznietsov et al. (2019) highlighted the application of AHP in solving complex system problems within the DSS NooTron system, showcasing its adaptability in dynamic hierarchical structures. Similarly, Liu

(2022) identified and corrected defects in the Saaty-ANP method, proposing a Markov Chain-based ANP to enhance decision-making accuracy. Trihapningsari et al. (2021) applied AHP in measuring IT governance capabilities using the COBIT 5 framework, proving its utility in evaluating IT service management processes.

Expanding on the applications of AHP, a study by Chengar et al. (2020) examined the primary processing of social network data using the hierarchy analysis method, highlighting its effectiveness in managing large datasets. Similarly, Guananga et al. (2019) applied AHP to evaluate process management systems, demonstrating high efficiency perceived by executives. Soylemez et al. (2021) applied AHP to supplier selection. Ivanovych Kuznietsov et al. (2019) further enhanced the AHP within the DSS NooTron system, showcasing its adaptability in complex system problem-solving.

Belousova and Bulgakova (2023) utilized AHP in inventory management within supply chains, employing a feedback method to efficiently address inventory issues based on a linear discrete system with a quadratic quality criterion. Pavlov and Kyselov (2023) discussed the application of AHP in coordinated planning within organizational and production systems at the top management level, highlighting its role in strategic decision-making. Zyubin et al. (2023) explored programming distributed control systems through a process-oriented paradigm, leveraging AHP for topologically independent control algorithm specification and formal verification methods, maintaining centralized program semantics.

Further, Wu et al. (2023) addressed a multi-factory production task allocation problem in make-to-order manufacturing using AHP to achieve balanced task allocation and cost optimization through an improved Non-Dominated Sorting Genetic Algorithm (NSGA-II) that integrates characteristics of the Ant Colony Optimization (ACO) algorithm. Dyumaeva and Kurochkin (2023) applied AHP for decision-making in selecting laboratory information management systems, examining a universal set of criteria suitable for most laboratories and evaluating the relative importance of these criteria.

3.3. ANP Literature

Liu (2022) conducted a comparative study revealing that the traditional Saaty-ANP lacks a mechanism to check the rationality of its structure, often leading to meaningless solutions, whereas the Markov chain-based ANP (MC-ANP) effectively addresses these issues by defining attributes and criteria relations through digraphs. Similarly, the study by Kuznietsov et al. (2019) demonstrated the flexibility of ANP within the DSS NooTron system for solving complex system problems, incorporating dynamic hierarchical structures. In the financial sector, Zakharov et al. (2019) found that a multilayer perceptron neural network integrated with ANP provides higher accuracy for time series forecasting, thereby enhancing decision-making processes.

Moreover, the use of ANP in evaluating IT governance capabilities has been significant, as illustrated by Trihapningsari et al. (2021), who applied ANP within the COBIT 5 framework to measure various IT service management processes. This application underscores the method's ability to handle intricate decision-making scenarios. Additionally, van der Aalst (2022) highlighted Europe's leadership in process management, attributing the region's dominance in the market to the extensive adoption of process mining technologies, where ANP played a crucial role in optimizing business processes and vendor evaluations. Tan et al. (2023) aim to select the most suitable active wheelchair for physically disabled individuals using the ANP, TOPSIS, and PROMETHEE methods. Five different wheelchair manufacturers' products were analyzed based on 18 criteria. Through these analyses and based on expert opinions, the most appropriate wheelchairs were identified. The study emphasizes that the choice of a wheelchair significantly affects the quality of life and health of users. The methods used, and the results obtained in the research aim to improve the living standards of physically disabled individuals.

Expanding on these applications, Antara et al. (2019) utilized ANP to assess the LAN network infrastructure of the Provincial Government of Bali, recommending improvements in specific domains to enhance network performance. This practical application showcases ANP's utility in infrastructure evaluation and development. Furthermore, Damigos et al. (2023) quantified the performance of 5G-enabled UAVs, using ANP to analyze critical parameters affecting real-life applications, thus demonstrating ANP's relevance in emerging technologies. Sheikh-Mohamed et al. (2023) employed ANP in power system operational planning, utilizing graph convolutional networks to predict the socio-economic costs of system strategies, enhancing efficiency for long-term development studies. Wang et al. (2023) proposed an integrated framework for neural network modelling and evaluation in nonlinear dynamic processes, using novel metrics like VAE-based KL divergence and the J metric to assess model accuracy, which was facilitated by the ANP method to incorporate multiple criteria. Similarly, Shvedov et al. (2023) optimized network routing in info-communication networks using the Markov decision process and Hamiltonian cycles, demonstrating the robustness of ANP in complex network environments.

Akinwale et al. (2023) developed a nature-based system survivability model using a prey-predator communal defense algorithm to protect the routing layer of the AODV protocol from intrusion attacks, achieving high throughput and rapid intrusion nullification, with ANP providing a structured approach to evaluating defense strategies. Sivapriya et al. (2023) dissected routing protocols in MANETs, examining the impact on network throughput by analyzing the interaction between QoS parameters and routing protocol selection, utilizing metrics such as average throughput, packet delivery ratio, and power consumption, with ANP facilitating the comprehensive evaluation of these parameters.

These studies highlight the diverse applications of ANP across different sectors, from IT governance and financial forecasting to process management and infrastructure evaluation. The consistent theme across these applications is ANP's ability to integrate multiple criteria and handle complex interdependencies, thereby providing robust and reliable decision-making frameworks. The fact that AHP and ANP methods have not been used as a hybrid before in the evaluation of fund criteria in the IRS is the motivation for this study.

4. AHP and ANP METHODOLOGIES

In this section, the proposed methodologies used in the study are explained in steps.

4.1. AHP Methodology

The AHP is a structured technique for organizing and analyzing complex decisions based on mathematics and psychology. Developed by Thomas L. Saaty in the 1980s, AHP is particularly useful in multi-criteria decision-making scenarios. Here are the steps involved in the AHP method (Saaty, 1980):

Step 1: Define the Problem and Determine the Goal

Clearly define the problem and state the goal of the decision-making process. This step involves identifying what needs to be decided and what the desired outcome is.

Step 2: Structure the Hierarchy

Break down the problem into a hierarchy of interrelated decision elements. The hierarchy typically consists of three levels:

1. The Goal: The overall objective of the decision.

2. Criteria: The factors that will influence the decision.

3. Alternatives: The different options available to achieve the goal.

Step 3: Construct Pairwise Comparison Matrices

For each level of the hierarchy, create pairwise comparison matrices. These matrices are used to compare the relative importance of each criterion and each alternative concerning each criterion. Decision-makers use a scale of 1 to 9 to express their preferences, where 1 indicates equal importance, and 9 indicates extreme importance of one element over another.

Step 4: Calculate the Priority Vectors

Normalize the comparison matrices and calculate the priority vectors (eigenvectors). This involves dividing each element of a column by the sum of the columns and then averaging the rows. The resulting vectors represent the relative weights of the criteria and the alternatives.

Step 5: Check for Consistency

Calculate the consistency ratio (CR) to ensure that the judgments made in the pairwise comparisons are consistent. This ratio can be calculated by using Equation 1. The CR is calculated by first determining the consistency index (CI) and then dividing it by the random consistency index (RI) for the corresponding matrix size. This index formulation is provided in Equation 2. A CR of 0.1 or less is considered acceptable. If the CR is higher, the comparisons should be revisited for consistency.

$$CR = \frac{CI}{RI} \tag{1}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

Step 6: Aggregate the Weights

Combine the priority vectors to determine the overall ranking of the alternatives. This is done by multiplying the weights of the criteria by the weights of the alternatives and summing up the results. The alternative with the highest aggregate weight is considered the best choice.

Step 7: Make the Decision

4.2. ANP Methodology

The ANP is an advanced method for decision-making that extends the capabilities of the AHP by incorporating interdependencies among decision criteria and alternatives. Developed by Thomas L. Saaty, ANP is particularly useful for complex decisions where interactions among elements are significant. Here are the steps involved in the ANP method (Saaty, 1996):

Step 1: Define the Problem and Determine the Goal

Clearly define the problem and state the goal of the decision-making process. This step involves identifying what needs to be decided and what the desired outcome is.

Step 2: Model the Network Structure

Develop a network structure that includes clusters of elements. Unlike AHP's hierarchical structure, ANP allows for a network of criteria and sub-criteria, which can have relationships among them. These clusters typically include:

1. The Goal: The overall objective of the decision.

2. Criteria: Factors that influence the decision.

3. Sub-criteria: Detailed elements under each criterion.

4. Alternatives: Different options are available to achieve the goal.

Step 3: Conduct Pairwise Comparisons within Clusters

For each cluster, conduct pairwise comparisons to determine the relative importance of elements. This involves comparing elements within the same cluster to assess their influence on the overall goal or on other elements within the network. The comparisons use a scale of 1 to 9, like AHP.

Step 4: Conduct Pairwise Comparisons between Clusters

Compare clusters to understand the influence of each cluster on others. This step accounts for the interdependencies and feedback among clusters, allowing the model to reflect the complex relationships in real-world decision-making.

Step 5: Form Supermatrix

Construct the Supermatrix, a large matrix that incorporates the results of all pairwise comparisons. The Supermatrix represents the relationships and influences among all elements in the network. Each sub-matrix within the supermatrix corresponds to a specific pairwise comparison set.

Step 6: Calculate the Weighted Supermatrix

Normalize the supermatrix by column so that the sum of each column is 1. This ensures that the weights are proportional and allows for a more accurate reflection of influences among elements. This matrix is calculated by using Equation 3.

$$W^* = W.D \tag{3}$$

where:

$W^*$is the weighted supermatrix,

W is the original supermatrix,

D is the diagonal matrix of cluster weights.

Step 7: Compute the Limit Supermatrix

Raise the weighted supermatrix to large powers (typically by multiplying it by itself multiple times) until it converges to a stable set of values. This process yields the limit supermatrix, which contains the long-term stable priorities of the elements. This matrix is calculated by using Equation 4.

$$W_\infty = \lim_{k\to\infty} (W^*)^k \tag{4}$$

Step 8: Synthesize Results

Analyze the limit supermatrix to determine the overall priorities of the alternatives. The elements with the highest priorities indicate the most favorable choices according to the network of criteria and sub-criteria.

Step 9: Make the Decision

Based on the synthesized results, make the final decision. The alternative with the highest priority in the limit supermatrix is considered the best choice.

5. EVALUATION OF FUND SELECTION CRITERIA USING AHP AND ANP METHODS

In this section of the study, a model has been proposed that considers the importance of the criteria used in fund selection and the interactions among these criteria.

In this study, a problem involving the criteria used by seven different fund managers, who are Decision-Makers (DM), in the IRS system for directing their funds is addressed. Table 1, Table 2, and Table 3 contain decision matrices belonging to three of seven DMs. The aim is to calculate the weights or importance levels of the criteria used by DM in managing their funds using the AHP method. The DM's are randomly selected individuals who manage their own IRS systems. These individuals are faculty-level individuals. Subsequently, the study seeks to measure the level of interaction among these criteria using the ANP method. The Criteria influence diagram is provided in Figure 1. The criteria identified by decision-makers in the study are as follows:

1. Risk Tolerance (CR_1): Assess your comfort with investment volatility. High-risk options may suit younger investors, while older investors might prefer stability.

2. Fund Performance (CR_2): Review historical performance to gauge how the fund has fared in various market conditions. Consistency is key.

3. Fund Fees and Expenses (CR_3): Examine management fees and expenses, as high costs can erode returns over time. Compare expense ratios across funds.

4. Fund Manager Experience (CR_4): Research the manager's track record and expertise. Experienced managers can add value through their market insights.

5. Diversification (CR_5): Ensure the fund offers diversification across asset classes. This mitigates risk by spreading investments.

6. Liquidity (CR_6): Evaluate how easily you can access your funds. Options for funds with reasonable liquidity terms to meet financial needs.

7. Investment Horizon (CR_7): Consider the time until retirement. Longer horizons can handle more risk, while shorter ones should focus on capital preservation.

Figure 1: Criteria influence diagram

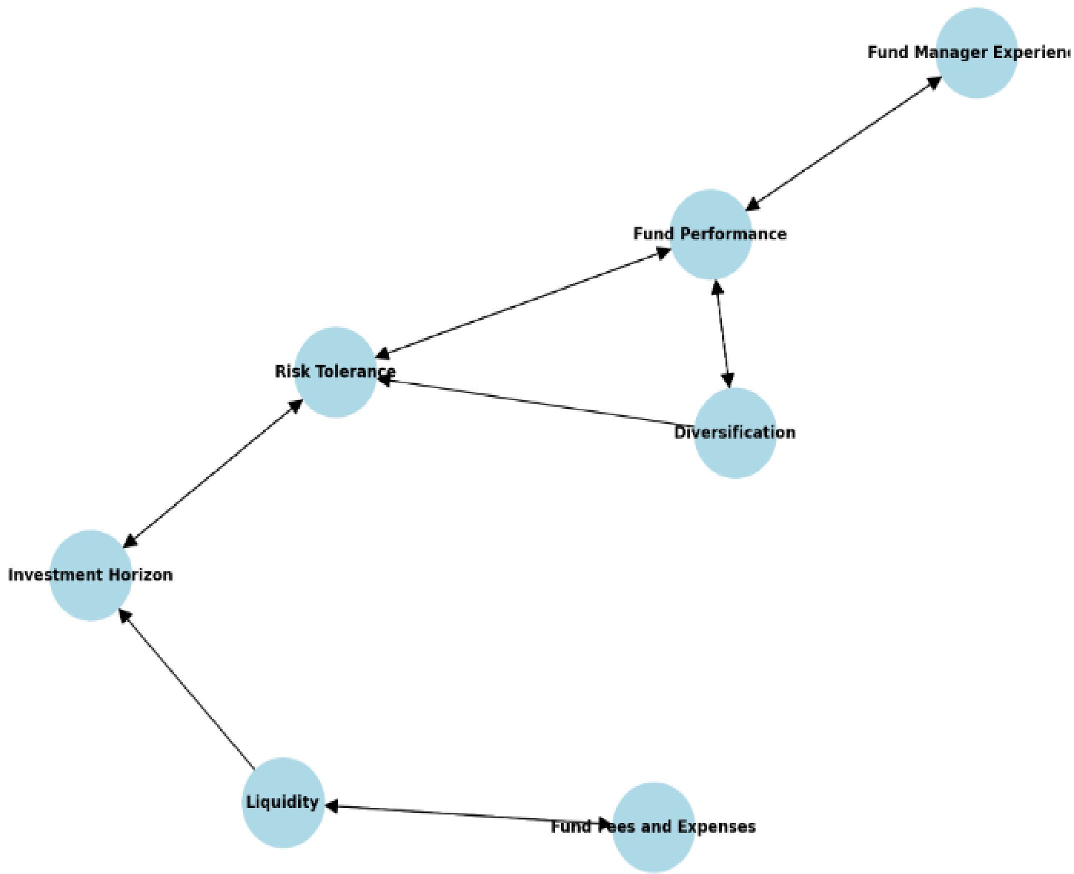

Table 1: DM_1 evaluation matrix

DM_1	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1	4	4	1/3	3	2	1
CR_2	1/4	1	3	1/4	4	4	1/5
CR_3	1/4	1/3	1	1/4	3	2	1/5
CR_4	3	4	4	1	4	5	1
CR_5	1/3	1/4	1/3	1/4	1	3	1/5
CR_6	1/2	1/4	1/2	1/5	1/3	1	1/5
CR_7	1	5	5	1	5	5	1

Table 2: DM_2 evaluation matrix

DM_2	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1	1	3	3	4	4	2
CR_2	1	1	4	2	4	4	1
CR_3	1/3	1/4	1	1/3	1	2	1/3
CR_4	1/3	1/2	3	1	5	4	1/2
CR_5	1/4	1/4	1	1/5	1	1/3	1/4
CR_6	1/4	1/4	1/2	1/4	3	1	1/3
CR_7	1/2	1	3	2	4	3	1

Table 3: DM_3 evaluation matrix

DM_3	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1	1/2	5	1	3	5	1
CR_2	2	1	5	2	5	5	2
CR_3	1/5	1/5	1	1/4	1	1/2	1/4
CR_4	1	1/2	4	1	4	4	1/2

CR_5	1/3	1/5	1	1/4	1	1/2	1/3
CR_6	1/5	1/5	2	1/4	2	1	1/4
CR_7	1	1/2	4	2	3	4	1

To obtain the joint evaluation of all decision-makers, the geometric mean of the matrices belonging to the seven decision-makers was calculated, and the resulting matrix is presented in Table 4. Using the matrix in Table 4, a normalization process was conducted, and the results are shown in Table 5. Finally, consistency was checked using eigenvalue, eigenvector calculations, and consistency ratio. It was observed that the consistency ratio is 0,06, which was less than 0.1 in the obtained results, indicating that the criterion weights are usable. Data regarding the criterion weights are provided in Table 6.

After calculating the criterion weights, it was observed that the highest weight is associated with criterion CR_1. Following that, criterion CR_2 has the next highest weight. In sequence, the other significant criteria are CR_7, CR_4, CR_6, CR_3, and CR_5.

The interactions between criteria have been calculated using the ANP (Analytic Network Process) method. The supermatrix is presented in Table 7. The weighted matrix is given in Table 8. The weighted super matrix is provided in Table 9, while the normalized weighted super matrix is provided in Table 10, and the Limit super matrix is provided in Table 11.

Table 4: Average values of DMs

Mean	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1,000	1,346	3,927	1,219	3,804	3,861	1,219
CR_2	0,743	1,000	4,054	1,292	4,544	4,263	0,969
CR_3	0,255	0,247	1,000	0,283	1,240	0,855	0,247
CR_4	0,820	0,774	3,536	1,000	4,401	4,263	1,060
CR_5	0,263	0,220	0,807	0,227	1,000	0,701	0,244
CR_6	0,259	0,235	1,170	0,235	1,426	1,000	0,229
CR_7	0,820	1,032	4,054	0,944	4,092	4,361	1,000
Total	**4,160**	**4,854**	**18,548**	**5,199**	**20,507**	**19,305**	**4,968**

Table 5: Normalization Matrix

Normalize	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	0,240	0,277	0,212	0,234	0,185	0,200	0,245
CR_2	0,179	0,206	0,219	0,248	0,222	0,221	0,195

CR_3	0,061	0,051	0,054	0,054	0,060	0,044	0,050
CR_4	0,197	0,159	0,191	0,192	0,215	0,221	0,213
CR_5	0,063	0,045	0,043	0,044	0,049	0,036	0,049
CR_6	0,062	0,048	0,063	0,045	0,070	0,052	0,046
CR_7	0,197	0,213	0,219	0,182	0,200	0,226	0,201

Table 6: Final Weights

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
Weights	0,2278	0,2127	0,0535	0,1984	0,0471	0,0552	0,2052

Table 7: Super Matrix

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1,00	0,00	0,00	0,00	0,14	0,17	0,00
CR_2	0,33	1,00	0,00	0,13	0,00	0,20	0,00
CR_3	0,20	0,20	1,00	0,00	0,00	0,00	0,00
CR_4	0,20	0,33	0,00	1,00	0,00	0,25	0,17
CR_5	0,13	0,00	0,00	0,00	1,00	0,00	0,00
CR_6	0,17	0,13	0,00	0,13	0,00	1,00	0,13
CR_7	0,25	0,25	0,00	0,00	0,00	0,14	1,00

Table 8: Weighted Matrix

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1,00	0,00	0,00	0,00	1,00	0,38	0,00
CR_2	0,25	1,00	0,00	0,13	0,00	0,23	0,00
CR_3	0,03	0,14	1,00	0,00	0,00	0,00	0,00
CR_4	0,13	0,17	0,00	1,00	0,00	0,16	0,83
CR_5	0,05	0,00	0,00	0,00	1,00	0,00	0,00

CR_6	0,24	0,09	0,00	0,87	0,00	1,00	0,17
CR_7	0,30	0,60	0,00	0,00	0,00	0,23	1,00

Table 9: Weighted Super Matrix

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	1,00	0,00	0,00	0,00	0,14	0,06	0,00
CR_2	0,08	1,00	0,00	0,02	0,00	0,05	0,00
CR_3	0,01	0,03	1,00	0,00	0,00	0,00	0,00
CR_4	0,03	0,06	0,00	1,00	0,00	0,04	0,14
CR_5	0,01	0,00	0,00	0,00	1,00	0,00	0,00
CR_6	0,04	0,01	0,00	0,11	0,00	1,00	0,02
CR_7	0,07	0,15	0,00	0,00	0,00	0,03	1,00
Total	1,24	1,25	1,00	1,13	1,14	1,18	1,16

Table 10: Normalized Weighted Super Matrix

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	0,81	0,00	0,00	0,00	0,13	0,05	0,00
CR_2	0,07	0,80	0,00	0,01	0,00	0,04	0,00
CR_3	0,01	0,02	1,00	0,00	0,00	0,00	0,00
CR_4	0,02	0,05	0,00	0,89	0,00	0,03	0,12
CR_5	0,01	0,00	0,00	0,00	0,88	0,00	0,00
CR_6	0,03	0,01	0,00	0,10	0,00	0,85	0,02
CR_7	0,06	0,12	0,00	0,00	0,00	0,03	0,86

Table 11: Limit Super Matrix

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
CR_1	0,231	0,231	0,231	0,231	0,231	0,231	0,231
CR_2	0,189	0,189	0,189	0,189	0,189	0,189	0,189
CR_3	0,081	0,081	0,081	0,081	0,081	0,081	0,081
CR_4	0,157	0,157	0,157	0,157	0,157	0,157	0,157
CR_5	0,053	0,053	0,053	0,053	0,053	0,053	0,053
CR_6	0,091	0,091	0,091	0,091	0,091	0,091	0,091
CR_7	0,193	0,193	0,193	0,193	0,193	0,193	0,193

Table 12: Final Evaluation

Criteria	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
ANP	0,231	0,189	0,081	0,157	0,053	0,091	0,193
AHP	0,227	0,212	0,053	0,198	0,047	0,055	0,205

Looking at the findings obtained through the ANP method, similar results to those from the AHP method can be noted. It has been found that the most important criterion is CR_1. The second most important criterion is CR_7. While in AHP, the second important criterion was CR_2, in ANP, it appears as the third most important criterion. Following these, CR_4, CR_6, CR_3, and CR_5 are identified as other significant criteria.

If we need to interpret the criteria differently, we can say that the most important criterion for an IRS investor is risk tolerance. Therefore, since the level of risk-taking can vary from person to person, the IRS system has emerged as the most important parameter to be considered in terms of risk and return at the point of preference. The next criterion is the return performance of the IRS fund to be selected. Unfortunately, today, due to the wrong fund selection, many investors' portfolios remain stagnant. For this reason, correct portfolio management according to fund performance is an important stage in obtaining the right return. The fund manager's experience has also been seen as another important criterion for you to maximize your income correctly. The liquidity of the fund is the next important criterion. Some IRS users are not very aware of the fees in the funds. Unfortunately, although this situation seems minor, it is another criterion to be considered. Diversification in funds is the last criterion to be considered.

5. CONCLUSION

Investing plays a crucial role in securing financial stability and building wealth over time. It allows individuals to grow their capital, providing a safety net for future needs and enabling them to achieve long-term financial goals. Within the broader spectrum of investment options, the IRS stands out as a structured way to ensure financial security in retirement. By contributing regularly to retirement funds, individuals benefit from compound interest, tax advantages, and employer contributions, significantly enhancing their retirement savings. However, selecting the right investment funds within the IRS requires careful consideration of various criteria, as different funds offer varying levels of risk and return potential. Understanding these criteria, such as risk tolerance, fund performance, and liquidity, enables investors to make informed decisions that align with their financial goals and timelines. Diversification across different asset classes is also essential, as it helps mitigate risk and increase the potential for higher returns. Thus, the individual retirement system, when navigated effectively, becomes a powerful tool for financial planning and retirement readiness.

In this study, we analyzed key criteria that influence fund selection within the individual retirement system using the AHP and ANP methodologies. The AHP was employed to structure and prioritize the criteria, providing a clear framework for decision-making. It allowed us to break down the complex decision into manageable parts, considering factors like risk tolerance, fund performance, and fees. The ANP method, on the other hand, captured the interdependencies among these criteria, offering a more nuanced analysis that reflects the real-world complexities of fund selection. Through these methods, we found that risk tolerance and fund performance were among the most influential criteria, while factors like liquidity and diversification also played significant roles. Our findings underscore the importance of a comprehensive approach to fund selection, considering both individual criteria and their interrelationships.

If we evaluate the results in the context of IRS funds and investors' financial behavior, the fact that investors are cautious in terms of risk tolerance can be interpreted as a negative situation in terms of being long-term investors. Since the IRS system is a long-term investment, having a high-risk tolerance can also offer the opportunity to benefit from possible high profits. The investment horizon criterion also emerges as an important criterion in this direction. Another element that investors care about is that they attach importance to the performance of the funds. This criterion can be evaluated together with the experience of the fund manager. While an inexperienced fund manager is likely to keep your IRS system far below your expectations, purchasing services from an experienced one will give you a much larger portfolio. Institutional preferences are important in this context. Diversification of investment and having different funds in the basket will also provide maximum benefit to investors in terms of absolute profit in the long term.

Future research can build on this work by exploring additional criteria that may impact investment decisions within the IRS, such as market trends or regulatory changes. Additionally, longitudinal studies could examine how these criteria evolve and how they affect investment outcomes in the long run. Further applications of AHP and ANP in different financial contexts, such as corporate investment decisions or personal financial planning, could provide deeper insights into their utility and effectiveness. Moreover, integrating advanced data analytics and machine learning techniques with AHP and ANP could enhance decision-making frameworks, offering personalized investment recommendations based on individual investor profiles and market conditions. Such advancements would significantly contribute to the field of financial decision-making, helping investors navigate the complexities of fund selection with greater confidence and precision.

REFERENCES

Abdel-aziem, A. H., Mohamed, H. K. and Abdelhafeez, A. (2023). Neutrosophic decision making model for investment portfolios selection and optimizing based on wide variety of investment opportunities and many criteria in market. *Neutrosophic systems with applications*, *6*, 32-38.

Akinwale, A., Olajubu, E. and Aderounmu, G. (2023). A prey-predator defence mechanism for ad hoc on-demand distance vector routing protocol. *Journal of Computing and Information Technology*,*30*(2), 67-83.

Antara, G. M. B., Linawati, L. and Wirastuti, N. (2019). Evaluasi infrastruktur jaringan lan opd pemprov bali dengan cobit 5.0 studi kasus: pemprov bali. *Jurnal Teknologi Informasi dan Ilmu Komputer*,6(1).

Belousova, E. P. and Bulgakova, I. (2023). Inventory management in supply chains based on a linear discrete system with a quadratic quality criterion. *Science and Education of the Bauman MSTU*, (26), 3, 47-62.

Bingley, P., Datta Gupta, N. and Pedersen, P. J. (2001). The effects of pension program incentives on retirement behavior in Denmark. *CLS Working Paper No. 01-08.*

Budiono, D. ve Martens, M. (2010). Mutual funds selection based on funds characteristics. *Journal of Financial Research*, 33(3), 313-330.

Chengar, O., Shevchenko, V., Maschenko, E., Moiseev, D. and Soina, A. S. (2020). Strategy for primary processing of social networks data using hierarchy analysis method. *Journal of Physics: Conference Series*, 1679(2), 022082.

Coetzee, N. (2013). Choosing your retirement income: Retirement planning. *Personal Finance*, *2013*(390), 4-5.

Consigli, G., Iaquinta, G., Moriggia, V., Tria, M. and Musitelli, D. (2012). Retirement planning in individual asset-liability management. *International Journal of Management*,*23*(4), 365-396.

Damigos, G., Lindgren, T., Sandberg, S., & Nikolakopoulos, G. (2023). Performance of sensor data process offloading on 5G-Enabled UAVs. *Sensors*, 23(2), 864.

Dyumaeva, I. V. and Kurochkin, A. V. (2023). Application of the analytic hierarchy process in selecting laboratory ınformation management systems. *Analytical Review*, (6), 462-466.

Ferreira, R., Almeida Filho, A. ve Souza, F. D. (2009). A decision model for portfolio selection. *Production*, 19(2), 340-355.

Fiala, P. and Borovička, A. (2015). Investment decision-making by a two-step multi-criteria procedure. *Technology for Business and Economics*.

Gale, W. ve John, D. C. (2018). State-sponsored retirement savings plans: New Approaches to Boost Retirement Plan Coverage. In *How Persistent Low Returns Will Shape Saving and Retirement*, 201-215. Oxford University Press.

Guananga, G. P. T., Leon, J. C. R., Falconi, A. F. I., Salazar, Á. G. C. And Sanipatin, E. L. R. (2019). La gestión por procesos un sistema de control eficiente en las empresas. *Ciencia digital*, *3*(2.6), 495-514.

Ivanovych Kuznietsov, V., Yevtushenko, H. and Andriukhina, M. V. (2019). Solving system problems of a complex structure using multi-criteria analysis methods in the DSS NooTron. *Science and Technology Journal, 3*(122), 140-152.

Kantarcı, T. and van Soest, A. (2013). Stated preference analysis of full and partial retirement in the United States. *CESR-Schaeffer Working Paper*, (2013-011).

Kuznietsov, V. I., Yevtushenko, H. and Andriukhina, M. V. (2019). Solving system problems of a complex structure using multi-criteria analysis methods in the DSS NooTron. *Системні технології,3*(122), 140-152.

Liu, Q. (2022). Identifying and Correcting the Defects of the Saaty Analytic Hierarchy/Network Process: A Comparative Study of the Saaty Analytic Hierarchy/Network Process and the Markov Chain-based Analytic Network Process. *Operations Research Perspectives*, *9*, 100244.

Miranda-Pinto, J. (2012). Does personalized pension projection affect the retirement decision? Superintendencia de Pensiones, Working Paper No.53.

Narayanamoorthy, V. and Aravanan, S. (2003). Multiplier approach - as a tool for investment decision. The Management Accountant, 39(3), 208- 210.

Olson, R. and Phillips, D. (2015). Let's save retirement. *Social Science Research Network*, *Paper No. 2450471*.

Pavlov, A. and Kyselov, M. (2023). Mathematical models and methods of coordinated planning. *Management of Development of Complex Systems*, (2), 1-10.

Palanisamy, B. and Selvam, M. (2011). Stock Selection Ability of Indian Mutual Fund Managers Under Conditional Models. *Social Science Research Network*, *Paper No.* 1875885.

Roon, F., Guo, J. and ter Horst, J. (2010). A Random Walk by Fund of Funds Managers? *Social Science Research Network*, *Paper No. 1571673*.

Romadona, D. (2019). Perancangan Sistem Pendukung Keputusan Pemilihan Kepala Sekolah Terbaik Tingkat Kabupaten Labuahan Batu Utara Menggunakan Metode Analytic Hierarchy Process (Ahp)(Studi Kasus Dinas Pendidikan Aek Natas). *Informasi dan Teknologi Ilmiah* (INTI), 7(1), 29-31.

Saaty, T. L. (1980). *The analytic hierarchy process:* planning, priority setting, resource allocation. New York: McGraw-Hill.

Saaty, T. L. (1996). Decisions with the analytic network process (ANP). *University of Pittsburgh (USA), ISAHP*, 96.

Sánchez, M. A., Milanesi, G. S. and Rivitti, M. B. (2010). Evaluación de alternativas de inversión utilizando el proceso jerárquico analítico. *Escritos Contables y de Administración*, *1*(2), 21-34.

Saraoglu, H. and Detzler, M. (2002). A sensible mutual fund selection model. *Financial Analysts Journal*, 58(3), 60-72.

Söylemez, E. Y., Kayabaşı, A. and Doğan, S. (2021). Seramik sektörü tedarikçi seçim sürecinde gri ilişkisel analiz (GİA) ile entegre edilmiş analitik hiyerarşi prosesi (AHP) modeli. *İzmir İktisat Dergisi*, 36(3), 497-516.

Shvedov, A. V., Gadasin, D. V., Klygina, O. G. and Tremasova, L. A. (2023, March). Optimization of Network Routing Using the Markov Decision Process and Hamiltonian Cycle. In *2023 Systems of Signals Generating and Processing in the Field of on Board Communications* (pp. 1-4). IEEE.

Sivapriya, N., Mohandas, R., Kumar, P. K., & Vaigandla, K. K. (2023). Dissection of Mobility Model Routing Protocols in MANET on QoS Criterion. *International Journal of Research in Information Technology and Computing*.

Sheikh-Mohamed, Y. B., Jakobsen, S. H., Bødal, E. F., Haugseth, F. M., Kiel, E. S. and Riemer-SØrensen, S. (2023, June). Graph Convolutional Networks for probabilistic power system operational planning. In *2023 IEEE Belgrade PowerTech* (pp. 1-6). IEEE.

Şahin, O., & Başarır, Ç. (2019). Bireysel emeklilik şirketlerinin finansal performanslarının değerlendirilmesi: Türkiye örneği. *Yönetim Bilimleri Dergisi*, *17*(33), 211-229.

Tan, M., Yazıcı, E. and Alakaş, H. M. (2023). Active Wheelchair Selection for the Physically Disabled with Analytical Network Process, TOPSIS, and PROMETHEE Methods. *International Journal of Pure and Applied Sciences, 9*(1), 76-87.

Trihapningsari, D., Agushinta, R. D. and Banowosari, L. Y. (2021). Pengukuran Kapabilitas Tata Kelola TI Sistem Informasi Tiras dan Transaksi Bahan Ajar Universitas Terbuka Menggunakan Cobit 5. *Jurnal Teknologi Informasi dan Ilmu Komputer*,8(5),965-976.

Van der Aalst, W. M. P. (2022). European leadership in process management. *ACM Transactions on Management Information Systems*,65(4),80-83.

Wang, Z., Liu, L., Dong, X. and Liu, J. (2023). Evaluation of neural network models and quality forecasting based on process time-series data. *Canadian Journal of Chemical Engineering*. *102*(4), 1522-1537.

Cheng, W., Wang, J. Y. and Ma, J. T. (2008). Optimal investment decision of security investment fund based on the experiment design. In *2008 International Conference on Risk Management & Engineering Management* (pp. 527-530). IEEE.Wilton, M. (1974). What you should know about pensions. *Managerial Finance*, 1(1), 56-67.

Wu, X., Lin, Y. and Lin, T. (2023). Collaborative Production Task Allocation Decision for Multi Smart Factory. *Proceedings of the IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, 1-6.

Zakharov, A., Vakhitov, G. and Enikeeva, Z. (2019). Neural Network Architecture Development for Time Series Forecasting. *Journal of Applied Computer Science & Mathematics*, 13(6), 5615-5620.

Zyubin, V., Ivanishkin, D. S. and Anureev, I. (2023). Towards Process-Oriented Programming Distributed Control Systems. *Proceedings of the IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, 1-6.