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The Use of Multi-Criteria Decision-Making Methods in Comparing Companies Listed on the BORSA ISTANBUL

Editor
Fatih GÜÇLÜ

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The Use of Multi-Criteria Decision-Making Methods in Comparing Companies Listed on the Borsa İstanbul

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PREFACE

MCDM methods have gained importance in financial decision-making, especially when dealing with multiple, often conflicting goals. These approaches offer a structured way to evaluate several criteria at once, making them crucial for comparing financial assets or selecting investment portfolios. By factoring in both quantitative and qualitative measures, MCDM gives investors and financial institutions a more thorough and organized path to make well-informed decisions. Its ability to adapt to the evolving demands of financial markets, such as sustainability, risk, and performance, makes it a valuable tool.

The book is divided into three chapters, each offering a unique perspective on how MCDM methods are applied to companies listed on Borsa İstanbul. The first chapter, authored by Furkan Göktaş and entitled "The MCDM Approaches for Portfolio Selection: An Application on BIST Participation Sustainability Index Stocks", examines two MCDM approaches, PES and R-FES, for portfolio selection. The study provides a comparative analysis of these methods using the BIST Participation Sustainability Index stocks, thus providing practical insights into portfolio optimization techniques.

In the second chapter, "An MCDM Approach for the Turkish Banks' FinTech Level Comparison", Hidayet Zahid Gürbüz employs MCDM to analyze the FinTech levels of Turkish banks traded on the BIST100. By comparing the rankings of banks based on AI-generated data, this chapter highlights the growing significance of FinTech in banking performance and competitiveness, contributing valuable information for strategic decision-making.

The third chapter, "An AI-Based MCDM Approach for Sustainable Portfolio Selection: An Application on BIST Participation Sustainability Index Stocks", by Feyzullah Esad Şekkeli, focuses on the use of AI in MCDM for sustainable portfolio selection. The chapter integrates return, risk, and ESG scores into the decision-making process, offering a modern perspective on how AI-based methods can be employed to create balanced, sustainable portfolios.

The chapters in this book aim to provide both academic and practical perspectives on the effective use of MCDM techniques in various financial contexts to support more informed, balanced, and strategic decision-making in the rapidly changing financial environment.

Editor

Assoc. Prof. Dr. Fatih GÜÇLÜ

Content

CHAPTER I

The MCDM Approaches for Portfolio Selection: An Application on BIST Participation Sustainability Index Stocks

Furkan GÖKTAŞ[1]

1. Introduction

Decision-making has been a part of the lives of human beings throughout history. Multi-criteria decision-making (MCDM) is a sub-discipline of operations research and a relatively new concept for decision-making. On the other hand, the number of MCDM methods and their extensions (for the fuzzy or multiple decision matrices) grows exponentially. This chapter focuses on PES (an MCDM method) and R-FES (a fuzzy MCDM method).

Due to its nature, portfolio selection is one of the most important decision-making problems. Thus, many portfolio selection models are proposed. Markowitz's (1952) mean-variance (MV) is the most known of these models. Jorion (1986) uses the

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Bayesian statistics for the MV framework. Konno and Yamazaki (1991) propose a mean-absolute deviation model. Young (1998) proposes a minimax model based on game theory. Krokhmal et al. (2001) use the Conditional Value at Risk (CVaR), a coherent risk measure, instead of the variance. Carlsson et al. (2002) propose the possibilistic MV model based on fuzzy set theory. Garlappi et al. (2007) propose the robust MV model based on uncertainty sets. Lutgens and Schotman (2010) propose a robust analysis using multiple experts for the MV framework. Göktaş and Duran (2019) propose a possibilistic MV model based on the Principal Components Analysis. Pedersen et al. (2021) propose a model with two objectives, maximizing the portfolio's Sharpe ratio and sustainability score. Göktaş (2023) proposes an orthogonal possibilistic MV model.

Like the above models based on optimization problems, MCDM methods or their extensions are used for portfolio selection. Saaty et al. (1980) use AHP, whereas Tiryaki and Ahlatcioğlu (2009) use fuzzy AHP based on triangular fuzzy numbers. Pospiech (2019) uses TOPSIS and fuzzy TOPSIS for fundamental analysis. Narang et al.'s (2021) hybrid fuzzy MCDM method is based on triangular fuzzy numbers, whereas Akbaş and Dalkılıç's (2021) hybrid fuzzy MCDM method is based on trapezoidal fuzzy numbers. Bisht and Kumar (2022) propose a hybrid fuzzy MCDM method for fundamental analysis, similar to that of Parkhid and Mohammadi (2022).

This chapter uses PES and R-FES for the portfolio selection problem. They depend on a strictly concave maximization problem, ensuring a unique solution. They use triangular fuzzy numbers with the possibilistic mean and variance definitions used by Göktaş and Duran (2019). On the other hand, from the optimization perspective, R-FES uses Lutgens and Schotman's (2010) robust analysis for the MV framework, whereas PES uses the classical MV framework. In addition, R-FES is implemented with special optimization software, whereas PES is implemented with MS Excel to find the known analytical solution. This study compares them for the portfolio selection problem with a real-world example. The BIST participation sustainability index stocks for the service sector are the alternatives. The criteria are the minimum, mean, maximum, and standard deviation statistics. The training period is the year 2021, whereas the testing period is the year 2022.

The rest of the chapter is organized as follows. Section 2.1 gives the theory of PES, whereas Section 2.2 gives the theory of R-FES. Section 3 uses these methods for the portfolio selection problem with a real-world example. Section 4 concludes the chapter.

2. Methods

2.1. Possibilistic Evaluation System (PES)

PES, proposed by Göktaş and Güçlü (2024), uses triangular fuzzy numbers. Figure 1 graphically shows the membership function of triangular fuzzy number (-0.5, 0, 1).

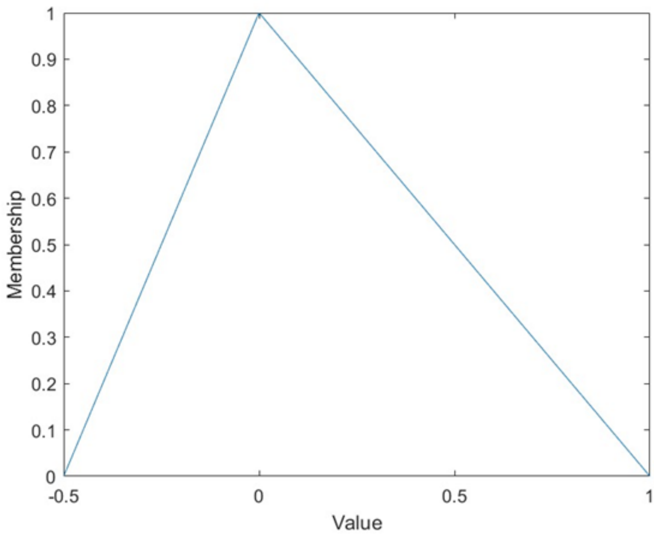

Figure 1: The graph of the membership function.

Let $A=(a_{ij})$ be the crisp decision matrix in Equation 1, where a_{ij} is its i^{th} row - j^{th} column element.

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{1}$$

The steps of PES are as below (Göktaş & Güçlü, 2024).

Step 1: The decision matrix (A) in Equation 1 is formed.

Step 2: The normalized decision matrix $B=(b_{ij})$ is formed using the ratio-based normalization in Equation 2, where b_{ij} is in [0,1]. α_j is the worst value for the j^{th} criterion (or equivalently the j^{th} column of A). β_j is the best value for the j^{th} criterion (or equivalently the j^{th} column of A). A and B matrices have m rows and n columns.

$$b_{ij} = \frac{|a_{ij} - \alpha_j|}{|\beta_j - \alpha_j|},\ for\ all\ i, j \tag{2}$$

Step 3: The criteria's weight vector $\lambda=(\lambda_j)$ is formed. (Here, AHP, Entropy, etc., can be used.) Its elements are nonnegative, whereas their sum equals 1.

The maximin rule reflects the pessimistic view and uses the security level ($B_{i,1}$) in Equation 3. It chooses the alternative having the maximum security level (Vaidogas et al., 2007).

$$B_{i,1} := \min_j b_{ij},\ for\ all\ i \tag{3}$$

The weighted sum method uses the weighted sum value ($B_{i,2}$) in Equation 4. It chooses the alternative having the maximum weighted sum value (Vaidogas et al., 2007).

$$B_{i,2} := \sum_{j=1}^{n} \lambda_j b_{ij},\ for\ all\ i \tag{4}$$

The maximax rule reflects the optimistic view and uses the optimism level ($B_{i,3}$) in Equation 5. It chooses the alternative having the maximum optimism level (Vaidogas et al., 2007).

$$B_{i,3} := \max_j b_{ij},\ for\ all\ i \tag{5}$$

Step 4: The fuzzy utility of the i^{th} alternative is determined as the triangular fuzzy number ($B_{i,1}$, $B_{i,2}$, $B_{i,3}$).

PES searches for Equation 6's unique optimal solution (w^*), where $w=(w_i)$ is the portfolio's weight vector. The objective function's numerator (denominator) term equals the portfolio's possibilistic mean (standard deviation) (Göktaş & Duran, 2019). Here, 1 is used instead of $B_{i,3}$ in the calculation of the portfolio's possibilistic standard deviation like in Equation 9 (Göktaş & Güçlü, 2024).

$$\max \frac{\sum_{i=1}^{m} w_i \left(\frac{B_{i,1} + 2B_{i,2} + B_{i,3}}{4} \right)}{\sqrt{\sum_{i=1}^{m} w_i^2 \left(\frac{1 - B_{i,1}}{6} \right)^2}} \tag{6}$$

$$s.t. \sum_{i=1}^{m} w_i = 1$$

$$w_i \geq 0 \; \textit{for all } i$$

After transforming Equation 6 into a strictly concave maximization problem, the i^{th} element of w^* is uniquely found as in Equation 7 using the Lagrange multipliers method. Clearly, w_i^* is a nonnegative and strictly increasing function of $B_{i,1}$, $B_{i,2}$, and $B_{i,3}$, respectively (Göktaş & Güçlü, 2024).

$$w_i^* = \frac{1}{\sum_{i=1}^{m} \frac{\left(B_{i,1} + 2B_{i,2} + B_{i,3}\right)}{\left(1 - B_{i,1}\right)^2}} \frac{\left(B_{i,1} + 2B_{i,2} + B_{i,3}\right)}{\left(1 - B_{i,1}\right)^2} \tag{7}$$

Step 5: The i^{th} alternative's priority value (p_i) is determined as $p_i = w_i^*$.

Step 6: The priority vector $p=(p_i)$ is used for resource allocation and/or ranking the alternatives.

2.2. Robust Theoretical Fuzzy Evaluation System (R-FES)

R-FES, proposed by Göktaş and Gökerik (2024), is a fuzzy MCDM method. It is used when the element of the fuzzy decision matrix (F) are triangular fuzzy numbers. Its steps are as below for the multiple decision matrices where any decision matrix may correspond to an expert's opinions, a time level of the panel data, etc.

Step 1: The multiple decision matrices $A_1, A_2, \ldots., A_k$ are formed.

Step 2: Each decision matrix is normalized separately using Equation 2 and the normalized decision matrices $B_1, B_2, \ldots., B_k$ are formed.

Step 3: The fuzzy decision matrix's (F) i^{th} row - j^{th} column element equals the triangular fuzzy number (c_{ij}, d_{ij}, e_{ij}) where c_{ij} / d_{ij} / e_{ij} is the minimum / median / maximum of the i^{th} row - j^{th} column elements of the normalized decision matrices.

Step 4: The nonnegative possibilistic mean matrix $M=(m_{ij})$ is formed using Equation 8.

$$m_{ij} =: E_p\left(\left(c_{ij}, d_{ij}, e_{ij}\right)\right) = \frac{c_{ij} + 2d_{ij} + e_{ij}}{4} \tag{8}$$

Step 5: The nonnegative possibilistic variance matrix $V=(v_{ij})$ is formed using Equation 9.

$$v_{ij} := Var_p\left(\left(c_{ij}, d_{ij}, 1\right)\right) = \left(\frac{1-c_{ij}}{6}\right)^2 \tag{9}$$

Equation 10 gives the portfolio (w^*) that maximizes the worst-case utility (y) for the different criteria where δ is the nonnegative risk-aversion coefficient, and the j^{th} constraint of Equation 10 is associated with the j^{th} criterion.

$$\max\ y$$

$$s.t.\ y - \left(\sum_{i=1}^{m} w_i m_{ij} - \frac{1}{2}\delta \sum_{i=1}^{m} w_i^2 v_{ij}\right) \leq 0,\ for\ all\ \ j \tag{10}$$

Since Equation 10 is a strictly concave maximization problem, its unique solution (w^*) can be found with the MATLAB software CVX (Grant & Boyd, 2008). The CVX code for Equation 10 is given in Equation 11 where δ equals 2 and λ_j is the Lagrange multiplier associated with the j^{th} constraint of Equation 10 (Göktaş & Gökerik, 2024).

$$
\begin{aligned}
&cvx\_solver\ mosek\\
&cvx\_begin\\
&variables\ w(m)\ y;\\
&dual\ variable\ \lambda;\\
&\quad maximize\,(y);\\
&\quad subject\ to\\
&\qquad \lambda:\ y*ones(n,1)-\begin{pmatrix} transpose(M)*w \\ -transpose(V)*(w.\wedge 2)\end{pmatrix} <= \ zeros(n,1);\\
&cvx\_end
\end{aligned}
\tag{11}
$$

Remark: λ_j values are nonnegative, and their sum equals 1. w_i^* values are inversely proportional to δ, which does not affect the Lagrange multipliers. Thus, δ is a scaling parameter. λ_j values affect w^* as the j^{th} constraint's weight (Lutgens & Schotman, 2010). Due to this information and the nonnegativity of the matrices, the w^* vector is found to be nonnegative (Göktaş & Gökerik, 2024).

Step 6: Equation 10 is solved for δ = 2 to find w_i^* and λ_j values. The j^{th} criterion's weight is objectively determined as λ_j.

Step 7: The i^{th} alternative's priority value (p_i) is found by standardizing w_i^* values as in Equation 12. (Since δ is a scaling parameter, it does not affect p_i and λ_j values.)

$$
p_i = \frac{w_i^*}{\sum_{i=1}^{m} w_i^*} \tag{12}
$$

Step 8: The priority vector $p=(p_i)$ is used for resource allocation and/or ranking the alternatives.

Remark: From the optimization perspective, Equation 6 corresponds to the tangency portfolio in the MV framework when the stock returns are uncorrelated. Equation 12 is the counterpart of this portfolio in Lutgens and Schotman's (2010) robust analysis for the MV framework.

3. Results and Discussion

In this section, we make an application on portfolio selection for the comparative analysis of PES and R-FES. We determine the criteria as the minimum statistic (C1), the mean statistic (C2), the maximum statistic (C3), and the standard deviation statistic (C4) based on Markowitz's MV model and the orthogonal possibilistic MV model (Göktaş & Güçlü, 2023). We use the sample estimators of these statistics. C1, C2, and C3 are utility criteria, whereas C4 is a cost criterion. The alternatives are the BIST participation sustainability index stocks for the service sector. For detailed information about this index, see Güçlü and Göktaş (2023). The alternatives are AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO. We use their simple returns, where the training (testing) period is the year 2021 (2022). We form the decision matrix in PES by using the data set for 2021, whereas we form the multiple decision matrix in R-FES using the data set for each quarter. That is why R-FES may capture the seasonality of these stocks in our application.

3.1. Possibilistic Evaluation System (PES)

We implement PES for the portfolio selection problem with the following steps.

Step 1: The decision matrix (A) is formed as in Table 1.

Table 1: The decision matrix (A) for PES.

	C1	C2	C3	C4
AKSEN	-0.1091	0.0208	0.1417	0.0577
BIMAS	-0.1534	-0.0033	0.1023	0.0379
DOAS	-0.1680	0.0107	0.2956	0.0737
ENJSA	-0.1312	0.0019	0.1280	0.0519
MAVI	-0.1616	0.0071	0.1216	0.0558
MPARK	-0.1524	0.0094	0.1223	0.0550
PGSUS	-0.0810	0.0044	0.2138	0.0646
THYAO	-0.0819	0.0100	0.2002	0.0575

Step 2: The normalized decision matrix is formed as in Table 2 using Equation 2.

Table 2: The normalized decision matrix (B) for PES.

	C1	C2	C3	C4
AKSEN	0.6763	1.0000	0.2038	0.4461
BIMAS	0.1678	0.0000	0.0000	1.0000
DOAS	0.0000	0.5810	1.0000	0.0000
ENJSA	0.4230	0.2153	0.1329	0.6078
MAVI	0.0738	0.4332	0.0998	0.4983
MPARK	0.1796	0.5254	0.1035	0.5214
PGSUS	1.0000	0.3208	0.5765	0.2547
THYAO	0.9889	0.5527	0.5065	0.4515

Step 3: The weights of the criteria are taken as equal.

Step 4: We determine the i^{th} alternative's fuzzy utility as $(B_{i,1}, B_{i,2}, B_{i,3})$ as in Table 3, where $B_{i,1}$ is the minimum element of the i^{th} row of B, $B_{i,2}$ is the average of the i^{th} row of B, and $B_{i,3}$ is the maximum element of the i^{th} row of B.

Table 3: The parameters of the triangular fuzzy numbers.

	$B_{i,1}$	$B_{i,2}$	$B_{i,3}$
AKSEN	0.2038	0.5816	1.0000
BIMAS	0.0000	0.2920	1.0000
DOAS	0.0000	0.3952	1.0000
ENJSA	0.1329	0.3448	0.6078
MAVI	0.0738	0.2763	0.4983
MPARK	0.1035	0.3325	0.5254
PGSUS	0.2547	0.5380	1.0000
THYAO	0.4515	0.6249	0.9889

Step 5: Using Equation 7, the priority values for AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO are found as 0.1489, 0.0632, 0.0714, 0.0759, 0.0523, 0.0642, 0.1674 and 0.3567 respectively.

Step 6: The priority values of the stocks are assigned as the portfolio weights of the stocks.

3.1. Robust Theoretical Fuzzy Evaluation System (R-FES)

Let QX be the X. quarter of the year 2021. We implement R-FES for the portfolio selection problem with the following steps.

Step 1: The decision matrix for each quarter is formed. For example, the decision matrix for Q1 is in Table 4.

Table 4: The decision matrix (A_1) for Q1.

	C1	C2	C3	C4
AKSEN	-0.0897	0.0388	0.1417	0.0655
BIMAS	-0.0343	-0.0044	0.0493	0.0243
DOAS	-0.1680	0.0057	0.0919	0.0725
ENJSA	-0.1312	0.0005	0.1280	0.0680
MAVI	-0.1616	-0.0051	0.0949	0.0618
MPARK	-0.1333	0.0073	0.1223	0.0663
PGSUS	-0.0810	0.0015	0.2138	0.0742
THYAO	-0.0819	0.0013	0.0967	0.0537

Step 2: The normalized decision matrix B_k is formed by normalizing A_k using Equation 2. For example, the normalized decision matrix for Q1 is in Table 5.

Table 5: The normalized decision matrix (B_1) for Q1.

	C1	C2	C3	C4
AKSEN	0.5861	1.0000	0.5618	0.1747
BIMAS	1.0000	0.0146	0.0000	1.0000
DOAS	0.0000	0.2460	0.2592	0.0333
ENJSA	0.2753	0.1282	0.4784	0.1233
MAVI	0.0481	0.0000	0.2772	0.2494
MPARK	0.2594	0.2809	0.4437	0.1587
PGSUS	0.6510	0.1490	1.0000	0.0000
THYAO	0.6438	0.1456	0.2884	0.4117

Step 3: The fuzzy decision matrix (F), consisting of triangular fuzzy numbers, is formed. The first parameters of the triangular fuzzy numbers are given with the matrix $C=(c_{ij})$ in Table

6, where c_{ij} is the minimum of the i^{th} row - j^{th} column elements of B_1, B_2,……, and B_k.

Table 6: The first parameters of the fuzzy decision matrix (F).

	C1	C2	C3	C4
AKSEN	0.0793	0.3509	0.2696	0.1624
BIMAS	0.0000	0.0000	0.0000	0.5653
DOAS	0.0000	0.0000	0.2592	0.0000
ENJSA	0.0000	0.0000	0.0000	0.1233
MAVI	0.0000	0.0000	0.0000	0.2188
MPARK	0.0511	0.2809	0.1242	0.1587
PGSUS	0.1773	0.0720	0.3910	0.0000
THYAO	0.5324	0.1343	0.2884	0.3456

The second parameters of triangular fuzzy numbers are given with the matrix $D=(d_{ij})$ in Table 7 where d_{ij} is the median of the i^{th} row - j^{th} column elements of B_1, B_2,……, and B_k.

Table 7: The second parameters of the fuzzy decision matrix (F).

	C1	C2	C3	C4
AKSEN	0.5060	0.8299	0.4548	0.3341
BIMAS	0.5203	0.0550	0.0637	0.9821
DOAS	0.1919	0.5282	0.7464	0.0167
ENJSA	0.2878	0.0930	0.2080	0.7072
MAVI	0.2431	0.3739	0.3334	0.3377
MPARK	0.3675	0.4646	0.4642	0.5379
PGSUS	0.6951	0.2288	0.7548	0.2729
THYAO	0.6279	0.4099	0.3994	0.4408

The third parameters of triangular fuzzy numbers are given with the matrix $E=(e_{ij})$ in Table 8 where d_{ij} is the maximum of the i^{th} row - j^{th} column elements of B_1, B_2,….., and B_k.

Table 8: The third parameters of the fuzzy decision matrix (F).

	C1	C2	C3	C4
AKSEN	1.0000	1.0000	0.5618	0.9454
BIMAS	1.0000	0.1072	0.4128	1.0000
DOAS	0.5416	1.0000	1.0000	0.2316
ENJSA	0.4105	0.5987	0.4784	1.0000
MAVI	0.7973	1.0000	0.8317	0.8410
MPARK	1.0000	0.6864	0.6135	0.8350
PGSUS	0.8308	0.6831	1.0000	0.5590
THYAO	0.9248	0.9621	0.5694	0.7132

Step 4: The possibilistic mean matrix (M) equals (C+2xD+E)/4 as in Table 9.

Table 9: The possibilistic mean matrix (M).

	C1	C2	C3	C4
AKSEN	0.5228	0.7527	0.4352	0.4440
BIMAS	0.5102	0.0543	0.1350	0.8824
DOAS	0.2313	0.5141	0.6880	0.0662
ENJSA	0.2465	0.1962	0.2236	0.6344
MAVI	0.3209	0.4369	0.3746	0.4338
MPARK	0.4465	0.4741	0.4165	0.5174
PGSUS	0.5996	0.3032	0.7252	0.2762
THYAO	0.6783	0.4790	0.4141	0.4851

Step 5: As shown in Table 10, the possibilistic variance matrix $V=(v_{ij})$ is formed using Table 6 where $v_{ij}=[(1-c_{ij})^2]/36$.

Table 10: The possibilistic variance matrix (V).

	C1	C2	C3	C4
AKSEN	0.0235	0.0117	0.0148	0.0195
BIMAS	0.0278	0.0278	0.0278	0.0052
DOAS	0.0278	0.0278	0.0152	0.0278
ENJSA	0.0278	0.0278	0.0278	0.0213
MAVI	0.0278	0.0278	0.0278	0.0170
MPARK	0.0250	0.0144	0.0213	0.0197
PGSUS	0.0188	0.0239	0.0103	0.0278
THYAO	0.0061	0.0208	0.0141	0.0119

Step 6: Using CVX code in Equation 11, we find the w_i^* values of AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO as 15.4104, 7.0641, 9.3215, 6.6381, 8.8157, 10.9811, 1.0219 and 13.4052 respectively. We also find $\lambda_1=0$, $\lambda_2=0.2962$, $\lambda_3=0.4045$ and $\lambda_4=0.2993$. That is, R-FES objectively determines the weight of C1 as 0, the weight of C2 as %29.62, the weight of C3 as %40.45 and the weight of C4 as %29.93.

Step 7. By normalizing the w_i^* values with Equation 12, we find the priority values of AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO as 0.1864, 0.0855, 0.1128, 0.0803, 0.1067, 0.1328, 0.1333 and 0.1622 respectively.

Step 8: The priority values of the stocks are assigned as the portfolio weights of the stocks.

3.3. Comparison of PES and R-FES

Table 11 gives the weight vectors obtained with PES and R-FES, whereas the equally weighted portfolio (EWP) and Young's (1998) minimax portfolio (YMP) are the benchmarks. (We choose YMP as a benchmark since it cannot implemented with negative stock weights like PES and R-FES.) YMP and R-FES are worst-case-oriented. On the other hand, R-FES gives more diversified portfolio than YMP.

Table 11: The weight vectors of the portfolios.

	PES	R-FES	YMP	EWP
AKSEN	0.1489	0.1864	0.2699	0.1250
BIMAS	0.0632	0.0855	0.1844	0.1250
DOAS	0.0714	0.1128	0.0000	0.1250
ENJSA	0.0759	0.0803	0.0000	0.1250
MAVI	0.0523	0.1067	0.0000	0.1250
MPARK	0.0642	0.1328	0.0000	0.1250
PGSUS	0.1674	0.1333	0.0000	0.1250
THYAO	0.3567	0.1622	0.5457	0.1250

Table 12 gives the results for the testing period. YMP has the first rank for C1, C2 and C3, whereas it has the last rank for C4. R-FES has the second rank for C1 and C4, whereas it has the third rank for C2 and C3. PES has the second rank for C2 and C3, whereas it has the third (last) rank for C4 (C1). EWP has the last rank for C2 and C3, whereas it has the first (third) rank for C4 (C1).

Table 12: The results for the testing period.

	C1		C2		C3		C4		Borda Count
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	
PES	-0.0627	4	0.0331	2	0.1574	2	0.0430	3	3
R-FES	-0.0586	2	0.0301	3	0.1171	3	0.0372	2	2
YMP	-0.0487	1	0.0337	1	0.1895	1	0.0464	4	1
EWP	-0.0615	3	0.0287	4	0.1139	4	0.0369	1	4

The Borda count is a simple method that combines different rankings based on the sum of each alternative's ranks (Aktaş & Demirel, 2021). Based on the Borda count method, the portfolios' general ranks are YMP, R-FES, PES, and EWP. Since R-FES captures the stocks' seasonality, it gives better results than PES. On the other hand, we note that PES may give different results for different criteria weights than the equal weighting. Since YMP is the only one considering the stocks' correlation structure, it has the first rank.

4. Conclusions

This chapter makes a comparative analysis of PES and R-FES for a portfolio selection problem. As discussed in the chapter, PES and R-FES have mutual and nonmutual points. For example, they give a unique nonnegative solution using triangular fuzzy numbers and the same possibilistic mean and variance definitions. Since PES uses a classical optimization framework, it is more practical and suitable for all decision-makers. On the other hand, R-FES uses a robust optimization framework, which considers higher-level information. Thus, it requires special optimization software. In addition, it may not be suitable for non-conservative decision-makers. In our application, Young's minimax portfolio (YMP) surpasses PES and R-FES. Since this chapter makes an in-sample analysis, these results can not be generalized. Furthermore, by changing the criteria, the methods may surpass YMP since they have the elasticity to consider different criteria, unlike YMP. Future research can consider the criteria based on quantitative, fundamental, or sustainability analyses. It can also consider the sensitivity analysis for PES.

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CHAPTER II

An MCDM Approach for the Turkish Banks’ FınTech Level Comparison

Hidayet Zahid GÜRBÜZ[1]

1. Introduction

Financial technologies (FinTech) have recently brought revolutionary changes to the banking sector. In addition to traditional banking systems, FinTech applications that offer digital solutions are widely used to increase customer experience and ensure operational efficiency (Karimi & Piri, 2020).

FinTech levels of banks are crucial for their success. The integration of FinTech into banking operations is essential for a bank's success, as it drives innovation, operational efficiency, and competitiveness. With technologies such as AI, Blockchain, and digital platforms, it is possible to improve customer satisfaction, processes, and risk management in banks. As the world of financing rapidly shifts, the level of FinTech adoption directly influences a

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bank's ability to remain relevant and competitive, making it a key factor in their long-term growth and sustainability. Thus, this chapter aims to compare the banks whose stocks are traded on BIST100 based on their FinTech levels. A multi-criteria decision-making (MCDM) method is used for this comparison, where data is obtained based on Gemini and ChatGPT-4o.

The importance of the chapter is based on understanding the strategic value of FinTech applications in the banking sector and shedding light on future research in this area. Understanding how FinTech affects the competitiveness of banks is important from both academic and practical perspectives. In this context, the findings in this chapter could help banks manage their digital transformation processes more effectively and make strategic decisions. At the same time, it can contribute to the shaping of regulations and policies in the sector by providing important information for policymakers and regulators (Wang & He, 2020).

This chapter is organized as follows. Section 2.1 summarizes FinTech and the banking sector. Section 2.2 summarizes MCDM methods for FinTech comparisons. Section 2.3 summarizes the FinTech applications in the Turkish banking sector. Section 3 summarizes the MCDM method (PES). Section 4 compares the banks whose stocks are traded on BIST100 in terms of their FinTech Levels. Section 5 discusses the results and concludes the chapter.

2. Conceptual Framework

2.1. FinTech and Banking Sector

Financial technologies (FinTech) mean reshaping traditional banking and financial services with digital solutions. FinTech radically changes how banks do business, allowing them to provide faster, more secure, and more user-friendly services. FinTech innovations have improved the financial system in many ways, including by lowering costs and providing higher-quality services as well as raising client happiness and involvement. It aids businesses in gaining a competitive edge and improving productivity (Kou et al., 2021). Moreover, Puschmann (2017) emphasizes that FinTech offers many advantages, such as reducing operational costs, shortening transaction times, and increasing customer satisfaction. For example, thanks to mobile banking applications, customers can perform banking transactions anywhere and anytime. This increases the competitiveness of banks and expands their customer base.

One of the most important components of the FinTech ecosystem is the business model. Researchers divided the FinTech business models into two categories: FinTech horizontals and FinTech verticals. FinTech horizontals, based on functional areas and developing technologies, are divided into two subcategories: the functional subtype and the technological subtype. FinTech verticals are based on financial services such as payments, wealth management, lending, insurance, capital markets, digital banking, and real estate business models (Imerman & Fabozzi, 2020).

According to Chen and Wu (2019), it increases effective consumer financing in China. The study's implementation of a SWOT analysis revealed that Fintech software applications significantly impact the credit system. Also, Chang et al. (2017) and Sun (2018) also emphasized the significance of Fintech investments in the functionality of such systems.

Gomber et al. (2018) state that FinTech enables banks to provide more personalized services, especially using big data analytics and artificial intelligence (AI) technologies. The research reveals that while digital transformation increases the quality of banks' customer service, it creates new challenges in data security and customer privacy. It is also stated that FinTech applications significantly improve banks' risk management and compliance processes. Moreover, Guo and Liang (2016), Du et al. (2019), and Eyal (2017) have also examined the significance of Fintech in the banking industry. Thanks to blockchain technology, they stated that the financial system could record client credit and payment information, among many other benefits.

FinTech solutions increase the operational efficiency of banks, reduce costs, and increase customer satisfaction. Lee and Shin (2018) emphasize that the FinTech ecosystem has transformed banks' business models, making financial services more accessible and user-friendly. In addition, technologies such as big data analytics and artificial intelligence have improved the quality of customer service and enabled banks to provide more personalized services (Gomber et al., 2017).

Banks face various challenges in the process of adopting FinTech applications. These challenges include factors such as regulation, data security, and technology adaptation. Arner et al. (2015) state that the innovations brought by FinTech also bring new regulatory needs. It can be seen that Turkish banks need flexible and innovative regulations to meet these challenges.

2.2. MCDM Methods for FinTech Comparisons

MCDM methods allow decision-makers to determine the most appropriate option by considering multiple criteria. MCDM methods simplify complex decision-making processes and enable objective evaluations. In a study conducted by Zavadskas and Turskis (2011), how MCDM methods are used in financial performance evaluations is examined in detail. The research shows that methods such as the Analytical Hierarchy Process (AHP) and TOPSIS effectively compare banks' FinTech performances. These methods help banks plan and implement their digital transformation strategies more effectively.

The AHP method simplifies the decision-making process within a hierarchical structure and helps determine the importance of the criteria. The TOPSIS method determines the most appropriate alternative by calculating the distances of the alternatives from the ideal solution and the negative ideal solution. These methods can be used to evaluate the effects of FinTech applications on the banking sector. For example, these methods can be used to evaluate a bank's mobile banking application on criteria such as customer satisfaction, transaction speed, cost-effectiveness, and security (Zavadskas & Turskis, 2011). Chatterjee et al. (2018) emphasize that the use of MCDM methods in FinTech evaluations plays a critical role in banks' gaining competitive advantage.

2.3. FinTech Applications in the Turkish Banking Sector

In the Turkish banking sector, the advent of FinTech applications has increased competition among players in the sector and improved customer experience notably. By transferring traditional banking to digital platforms, fintech firms provide quicker, more straightforward, and consumer-friendly services for their clients. Particularly, mobile banking, digital payment systems, blockchain technologies, and artificial intelligence-based solutions feature as key aspects of fintech applications in the Turkish banking industry (Genc, 2021).

Mobile banking and digital payment systems are among the most widely used areas of fintech applications. These systems enable customers to perform their banking transactions via mobile devices, shortening transaction times and facilitating access to banking services. At the same time, blockchain technologies developed by fintech companies make significant contributions to data security and transparency in the banking sector (Soylemez, 2020).

Regulatory authorities have additionally promoted the growth of fintech in Turkey. The legal frameworks for online banking have ensured safety and efficiency for players in the industry. These rules stimulate fintech innovations and fast-track digitalization of Turkish banks (Bayram et al., 2022).

The Turkish banking sector is rapidly adopting and integrating FinTech applications. A study conducted by Demirgüç-Kunt and Klapper (2012) analyzed the level of adoption of FinTech applications by Turkish banks and the impact of these applications on bank performance. The study concluded that Turkish banks have increased customer satisfaction, reduced transaction costs, and improved operational efficiency through FinTech applications. FinTech applications widely used in the Turkish banking sector include mobile banking, digital payments, blockchain technology, robo-advisory, and crowdfunding. These applications accelerate banks' digital transformation processes and increase their competitiveness.

Güneş and Aydın (2018) examine the fintech integration process of banks in Turkey, analyzing the role of regulation and market dynamics in this process. The study presents the challenges Turkish banks face in the digital transformation process and various suggestions on how to overcome these challenges. In particular, blockchain technology's benefits of security and transparency in financial transactions are highlighted.

The impact of FinTech on banks' business models has become more evident with the change in customers' expectations and the increase in digital services. In this context, assessing the FinTech performance of Turkish banks and making strategic decisions in light of these assessments is important for banks to achieve sustainable competitive advantage (Demirgüç-Kunt & Klapper, 2012). Furthermore, Dincer and Yüksel (2019) draw attention to the importance of technological investments and human resources in the FinTech adaptation process of Turkish banks. In this process, it is emphasized that banks should continuously invest in R&D activities in order to increase their innovation capabilities.

Banks face various challenges in the process of adopting FinTech applications. These challenges include factors such as regulation, data security, and technology adaptation. Arner et al. (2015) state that the innovations brought by FinTech also bring new regulatory needs. It can be seen that Turkish banks need flexible and innovative regulations to meet these challenges.

The following recommendations can be made for Turkish banks to be successful in their adoption and integration processes of FinTech applications:

• Innovative and flexible regulations: Flexible and innovative regulations are needed to overcome the regulatory challenges faced by banks in their FinTech application adoption processes. Regulators should develop policies that support FinTech innovation and facilitate banks' digital transformation processes (Arner et al., 2015).

• Develop digital capabilities: Banks need to develop their digital capabilities and develop innovative solutions. In this context, it is important for banks to continuously invest in R&D activities and effectively manage their digital transformation processes (Dincer & Yüksel, 2019).

• Collaborations and partnerships: Establishing collaborations and partnerships with startups in the FinTech ecosystem will be an important strategy for banks to enhance their innovation capabilities. Such collaborations will help banks to develop innovative solutions and gain competitive advantage.

• Sustainability perspective: Banks need to consider FinTech applications from a sustainability perspective. FinTech solutions can help create a sustainable financial system by contributing to environmental, social, and governance (ESG) factors (Schindler, 2017).

3. Method

This section summarizes the MCDM method (PES), which depends on three variables: security degree, average degree, and optimism degree. Its steps are as below for the equally weighted criteria (Güçlü & Göktaş, 2023; Göktaş & Güçlü, 2024).

Step 1: Determine the decision matrix $D=(d_{ij})$.

Step 2: Use (1) to get the normalized decision matrix $N=(n_{ij})$, where W_j is the worst element for the j^{th} criterion, and B_j is the best element for the j^{th} criterion.

$$n_{ij} = \left| \frac{d_{ij} - W_j}{B_j - W_j} \right| \tag{1}$$

Step 3: The minimum of the i^{th} row of N equals the security degree (s_i). The average of the i^{th} row of N equals the average degree (a_i). The maximum of the i^{th} row of N equals the optimism degree (o_i).

Step 4: Use (2) to calculate the priority degree (p_i).

$$p_i = \left(\sum_i \frac{(s_i + 2a_i + o_i)}{(1 - s_i)^2} \right)^{-1} \frac{(s_i + 2a_i + o_i)}{(1 - s_i)^2} \tag{2}$$

Step 5: Use the priority degrees to rank the alternatives in descending order.

4. Results

This section deals with the MCDM problem using PES based on Gemini and ChatGPT-4o. This MCDM problem is to compare the banks based on their FinTech levels. The alternatives are the banks whose stocks are traded on BIST100. The BIST codes of them are used in this chapter. The criteria are the four basic banking functions (payments, lending, financing, asset management & investment advice).

The steps of PES for this MCDM problem based on Gemini data are as follows where 10 corresponds to the best alternative and 1 corresponds to the worst alternative.

Step 1: The decision matrix is formed.

Table 1: The decision matrix I.

	Payments	Lending	Funding	A.M. & I.A.
AKBNK	8	6	7	9
ALBRK	5	9	4	10
GARAN	10	7	8	6
HALKB	7	8	9	4
ICBCT	1	2	2	3
ISCTR	9	5	10	5
SKBNK	2	1	3	1
TSKB	3	4	1	2
VAKBN	4	3	6	8
YKBNK	6	10	5	7

Step 2: The normalized decision matrix is formed using (1).

Table 2: The normalized decision matrix I.

	Payments	Lending	Funding	A.M. & I.A.
AKBNK	0.778	0.556	0.667	0.889
ALBRK	0.444	0.889	0.333	1.000
GARAN	1.000	0.667	0.778	0.556
HALKB	0.667	0.778	0.889	0.333
ICBCT	0.000	0.111	0.111	0.222
ISCTR	0.889	0.444	1.000	0.444
SKBNK	0.111	0.000	0.222	0.000
TSKB	0.222	0.333	0.000	0.111
VAKBN	0.333	0.222	0.556	0.778
YKBNK	0.556	1.000	0.444	0.667

Step 3: Security, average, and optimism degrees are calculated.

Table 3: The variables for PES I.

	Security D.	Average D.	Optimism D.
AKBNK	0.556	0.722	0.889
ALBRK	0.333	0.667	1.000
GARAN	0.556	0.750	1.000
HALKB	0.333	0.667	0.889
ICBCT	0.000	0.111	0.222
ISCTR	0.444	0.694	1.000
SKBNK	0.000	0.083	0.222
TSKB	0.000	0.167	0.333
VAKBN	0.222	0.472	0.778
YKBNK	0.444	0.667	1.000

Step 4-5: Priority degrees are calculated using (2). The alternatives are ranked using them. GARAN ranks first, whereas SKBNK ranks tenth.

Table 4: Performance degrees and the alternatives' ranks I.

	Priority D.	Rank
AKBNK	0.2259	2
ALBRK	0.0927	5
GARAN	0.2389	1
HALKB	0.0888	6
ICBCT	0.0069	9
ISCTR	0.1418	3
SKBNK	0.0060	10
TSKB	0.0103	8
VAKBN	0.0497	7
YKBNK	0.1390	4

The steps of PES for this MCDM problem based on ChatGPT-4o data are as follows, where 10 corresponds to the best alternative, and 1 corresponds to the worst alternative.

Step 1: The decision matrix is formed.

Table 5: The decision matrix II.

	Payments	Lending	Funding	A.M. & I.A.
AKBNK	9	7	8	9
ALBRK	5	6	7	4
GARAN	10	9	10	10
HALKB	2	2	1	3
ICBCT	1	1	2	2
ISCTR	8	8	9	8
SKBNK	3	3	3	1
TSKB	4	5	5	5
VAKBN	6	4	4	6
YKBNK	7	10	6	7

Step 2: The normalized decision matrix is formed using (1).

Table 6: The normalized decision matrix II.

	Payments	Lending	Funding	A.M. & I.A.
AKBNK	0.889	0.667	0.778	0.889
ALBRK	0.444	0.556	0.667	0.333
GARAN	1.000	0.889	1.000	1.000
HALKB	0.111	0.111	0.000	0.222
ICBCT	0.000	0.000	0.111	0.111
ISCTR	0.778	0.778	0.889	0.778
SKBNK	0.222	0.222	0.222	0.000
TSKB	0.333	0.444	0.444	0.444
VAKBN	0.556	0.333	0.333	0.556
YKBNK	0.667	1.000	0.556	0.667

Step 3: Security, average, and optimism degrees are calculated.

Table 7: The variables for PES II.

	Security D.	Average D.	Optimism D.
AKBNK	0.667	0.806	0.889
ALBRK	0.333	0.500	0.667
GARAN	0.889	0.972	1.000
HALKB	0.000	0.111	0.222
ICBCT	0.000	0.056	0.111
ISCTR	0.778	0.806	0.889
SKBNK	0.000	0.167	0.222
TSKB	0.333	0.417	0.444
VAKBN	0.333	0.444	0.556
YKBNK	0.556	0.722	1.000

Step 4-5: Priority degrees are calculated using (2). The alternatives are ranked using them. GARAN ranks first, whereas ICBCT ranks tenth.

Table 8: Performance degrees and the alternatives' ranks II.

	Priority D.	Rank
AKBNK	0.0657	3
ALBRK	0.0104	5
GARAN	0.7156	1
HALKB	0.0010	9
ICBCT	0.0005	10
ISCTR	0.1530	2
SKBNK	0.0013	8
TSKB	0.0084	7
VAKBN	0.0092	6
YKBNK	0.0350	4

It is noticed that the rankings based on Gemini and ChatGPT-4o data are different. On the other hand, the linear correlation coefficient between these rankings is 0.891. Thus, these experts (AI chatbots) present different but very similar rankings for the MCDM problem.

5. Discussion and Conclusions

In this chapter, an MCDM method (PES) is used to compare the FinTech levels of Turkish banks. The banks' performances are evaluated based on the data obtained from Gemini and ChatGPT-4o sources. The FinTech levels of the banks listed on the BIST100 are compared based on four basic banking functions (payments, lending, financing, asset management & investment advice).

In the analysis based on Gemini data, GARAN ranks first, while SKBNK ranks last. In the analysis based on ChatGPT-4o data, GARAN ranks first, while ICBCT bank ranks last. These analyses reveal that the FinTech level of GARAN is the highest. The rankings obtained with different AI chatbots are very similar since their linear correlation coefficient is close to 1. On the other hand, the rankings have some differences. For example, AKBNK ranks second based on Gemini data and third based on ChatGPT-4o data. In addition, ISCTR ranks third based on Gemini data and second based on ChatGPT-4o data.

Based on two different rankings, GARAN, AKBNK, ISCTR, YKBNK, and ALBRK are in the first five rows, whereas VAKBN, HALKB, TSKB, SKBNK, and ICBCT are in the last five rows. Thus, these banks could be separated into two main categories in terms of their FinTech levels. In a study examining banks' performances, the best banks for the year 2017 are AKBNK, Ziraat Bank, GARAN, and ISCTR, respectively. Ziraat Bank, AKBNK, and ISCTR are again in the top three for the year 2016. Ziraat Bank, AKBNK, GARAN, and ISCTR share the top four rows for the year 2015 (Sarı, 2020). Moreover, in another study that evaluated the performance of the top 8 banks in terms of asset size, GARAN, AKBNK, ISCTR, and YKBNK are the banks that managed to remain among the top 8 banks for the last 5 years (Gülsün & Erdoğmuş, 2021). As expected, a higher FinTech level improves the Turkish banks’ performance.

There are three different limitations of this study. First, the results could change when different MCDM methods or criteria weights are used. Second, the results are subjective since they depend on expert knowledge (AI chatbots). Third, the number of banks compared in this chapter is just 10. Future research could increase the number of banks, experts and MCDM methods. Furthermore, sensitivity analysis could be done for the criteria weights.

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CHAPTER III

An AI-Based MCDM Approach for Sustainable Portfolio Selection: An Application on BIST Participation Sustainability Index Stocks

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1. Introduction

The primary objective of portfolio selection theory is to achieve the highest return for the level of risk assumed with the capital held. The traditional portfolio theory (TPT) suggests that portfolio management is more of an art than a science and believes that simply increasing the number of samples randomly, known as "naive diversification," is sufficient to reduce risk (Saraç, 2017). TPT emerged at the beginning of the 20th century and played a crucial role in finance until the publication of Markowitz's "Modern Portfolio Theory (MPT)" in 1952 (Leković, 2021). In MPT, the mean-variance principle is used to assess the relationships between the returns of stocks through the covariance coefficient to determine the portfolio's risk level. Including stocks with negative correlations

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in the portfolio reduces unsystematic risk and increases the overall portfolio return (Acar & Ünal, 2022). However, researchers have encountered difficulties in applying the mean-variance model and have proposed various alternative solutions (Rustem et al., 2000; Tütüncü & Koenig, 2004). Nevertheless, these proposed solutions are merely variations of the mean-variance model and often neglect sustainability considerations.

The sustainability issue is essential for socially responsible investors. The environmental, social, and governance (ESG) score is an indicator of corporate sustainability (Ok & Göktaş, 2024). There are lots of studies that use multi-criteria decision-making (MCDM) methods or consider the ESG score in portfolio selection (Göktaş, 2024a; Göktaş, 2024b; Göktaş & Güçlü, 2024). This chapter uses an MCDM method to integrate the ESG score into the portfolio selection problem.

This chapter considers three criteria (return, risk, and ESG score) for the sustainable portfolio selection problem by using three AI chatbots (Gemini, Copilot, and ChatGPT-4o) as experts. The alternatives are the BIST Participation Sustainability Index service sector stocks (AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO). The generalization of the Simple Additive Weighting (SAW) method for uncertain criteria weights is used for the solution of MCDM problems. This MCDM method is called as U-SAW (Göktaş, in press).

This study examines the implementation of an AI-based MCDM approach for sustainable portfolio selection, specifically applied to the BIST Participation Sustainability Index stocks. The importance of this research lies in its attempt to explore a different approach from traditional portfolio optimization methods by enabling investors to develop more comprehensive and innovative portfolio strategies that integrate the ESG score. The results indicate that the AI-based MCDM approach effectively constructs optimal portfolios by incorporating the ESG score, thereby facilitating more balanced and sustainable investment decisions than conventional methodologies.

This chapter is organized as follows. Section 2.1 presents the BIST Participation Sustainability Index. Section 2.2 presents the ESG criteria. Section 3 presents U-SAW. Section 4 uses U-SAW for sustainable portfolio selection. Section 5 concludes the chapter.

2. Conceptual Framework

2.1. BIST Participation Sustainability Index

The BIST Participation Index is based on the participation finance criteria established by the Advisory Board of the Participation Banks Association of Turkey (TKBB) and published under the titles "Standard for Issuance and Trading of Shares" (Standard) and "Guideline for Identifying Companies Operating in Compliance with Participation Finance Principles" (Guideline). The purpose of this index is to provide an opportunity for investors who wish to invest within the framework of participation finance and to increase the awareness of companies regarding these principles (BIST, 2024a).

The BIST Sustainability Index, established by Borsa Istanbul in 2014, aims to communicate companies' sustainability efforts in the environmental, social, and corporate governance domains to investors who prioritize these principles. Since 2021, the scores calculated by Refinitiv, a globally recognized market data and infrastructure provider, have been used to evaluate companies included in the index (BIST, 2024b).

Since 2021, the BIST Participation Sustainability Index has begun listing companies that meet the criteria of both the BIST Participation Index and the BIST Sustainability Index. This index provides new opportunities for investors who have Islamic sensitivities and who, as responsible investors, also prioritize sustainability (Güçlü & Göktaş, 2023).

2.2. ESG Criteria

The concept of ESG was formally introduced in 2004, following an initiative by Kofi Annan, the then Secretary-General of the United Nations, to promote ethical investment practices. Responding to this call, a group of 18 financial institutions from nine countries collaborated on the report. This report highlighted the importance of incorporating ESG factors into investment decisions, marking the first structured articulation of the ESG framework. After that, in 2006, the United Nations introduced the Principles for Responsible Investment (PRI) to help investors recognize the importance of ESG factors and encourage their integration into investment strategies. (Shen et al., 2023). ESG is a tool for investors to assess corporate behavior and predict future financial performance. As a framework for evaluating sustainable development, its three core factors that are environmental (E), social (S), and governance (G), are critical in investment analysis and decision-making (Li et al., 2021).

The construction of ESG criteria involves key environmental, social, and governance factors. Environmental factors (E) focus on resource use, emissions, and innovation. Social factors (S) encompass workforce practices, human rights, community engagement, and product responsibility. Governance factors (G) encompass the management structure, relationships with shareholders, and the implementation of corporate social responsibility (CSR) strategies (LSEG, 2024). Together, these elements form the foundation for evaluating corporate sustainability and responsible investment practices, guiding investors in their decision-making processes.

3. Method

U-SAW determines the alternatives' priorities as SAW. The only difference between them is that U-SAW determines the criteria weights inherently, unlike SAW. The steps of U-SAW are as follows (Göktaş, in press).

Step 1: The decision matrix $A=(a_{ij})$ is formed. It is assumed that its elements are positive. 1/x transformation is done for cost criteria.

Step 2: (1) is used to get the normalized decision matrix $B=(b_{ij})$.

$$b_{ij} = \frac{a_{ij}}{\sum_{i} a_{ij}} \quad (1)$$

Step 3: y is a scaler variable, and $w=(w_i)$ is a vector variable. The alternatives' priority vector (w^*) is determined as the optimal solution of (2). The dual optimal vector of (2) is determined as the criteria weight vector (λ). As in the SAW, the alternatives' priority vector equals Bλ. Since (2) is a convex optimization problem, it can be solved using CVX (Grant & Boyd, 2008).

$$\begin{aligned} &\max\ y - \frac{1}{2}\sum_i w_i^2 \\ &s.t.\ y - \sum_i b_{ij} w_i \leq 0,\ for\ all\ \ j \end{aligned} \tag{2}$$

Step 4: The priority values are used for resource allocation to the alternatives or ranking the alternatives in descending order.

4. Results and Discussion

This section uses the latest ESG ranks of the alternatives, where 8 corresponds to the best ESG score, and 1 corresponds to the worst ESG score (LSEG, 2024). The experts' predictions for each alternative-criterion pair about the 19.08.2024-31.12.2024 period are taken using a 1 to 8 scale, where 8 corresponds to the best value, and 1 corresponds to the worst value. The investor is assumed to demand a high daily average return and low risk (the standard deviation of the daily returns).

Using Gemini predictions for the first two criteria and LSEG data for the ESG criterion, the steps of U-SAW for the sustainable portfolio selection problem are as follows.

Step 1: A is formed.

Table 1: The decision matrix I.

	Return	Risk	ESG
AKSEN	5	6	1
BIMAS	7	4	3
DOAS	2	7	6
ENJSA	4	3	7
MAVI	8	2	8
MPARK	1	8	2
PGSUS	3	5	4.5
THYAO	6	1	4.5

Step 2: B is formed using (1).

Table 2: The normalized decision matrix I.

	Return	Risk	ESG
AKSEN	0.139	0.167	0.028
BIMAS	0.194	0.111	0.083
DOAS	0.056	0.194	0.167
ENJSA	0.111	0.083	0.194
MAVI	0.222	0.056	0.222
MPARK	0.028	0.222	0.056
PGSUS	0.083	0.139	0.125
THYAO	0.167	0.028	0.125

Step 3: The priority values and criteria weights are found by solving (2). The weight of the return criterion equals 0.3544. The weight of the risk criterion equals 0.4424. The weight of the ESG criterion equals 0.2031.

Table 3: The priority values I.

	Weight	Rank
AKSEN	0.1286	4
BIMAS	0.1350	3
DOAS	0.1396	2
ENJSA	0.1157	7
MAVI	0.1485	1
MPARK	0.1195	5
PGSUS	0.1164	6
THYAO	0.0968	8

Step 4: The weights of AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO are 0.1286, 0.1350, 0.1396, 0.1157, 0.1485, 0.1195, 0.1164, and 0.0968 respectively. The best alternative is MAVI, whereas the worst alternative is THYAO.

Using Copilot predictions for the first two criteria and LSEG data for the ESG criterion, the steps of U-SAW for the sustainable portfolio selection problem are as follows.

Step 1: A is formed.

Table 4: The decision matrix II.

	Return	Risk	ESG
AKSEN	5	5	1
BIMAS	6	3	3
DOAS	3	6	6
ENJSA	4	4	7
MAVI	1	8	8
MPARK	2	7	2
PGSUS	7	2	4.5
THYAO	8	1	4.5

Step 2: B is formed using (1).

Table 5: The normalized decision matrix II.

	Return	Risk	ESG
AKSEN	0.139	0.139	0.028
BIMAS	0.167	0.083	0.083
DOAS	0.083	0.167	0.167
ENJSA	0.111	0.111	0.194
MAVI	0.028	0.222	0.222
MPARK	0.056	0.194	0.056
PGSUS	0.194	0.056	0.125
THYAO	0.222	0.028	0.125

Step 3: The priority values and criteria weights are found by solving (2). The weight of the return criterion equals 0.4712. The weight of the risk criterion equals 0.4516. The weight of the ESG criterion equals 0.0772.

Table 6: The priority values II.

	Weight	Rank
AKSEN	0.1303	2
BIMAS	0.1226	6
DOAS	0.1274	3
ENJSA	0.1175	8
MAVI	0.1306	1
MPARK	0.1183	7
PGSUS	0.1264	5
THYAO	0.1269	4

Step 4: The weights of AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO are 0.1303, 0.1226, 0.1274, 0.1175, 0.1306, 0.1183, 0.1264, and 0.1269 respectively. The best alternative is MAVI, whereas the worst alternative is ENJSA.

Using ChatGPT-4o predictions for the first two criteria and LSEG data for the ESG criterion, the steps of U-SAW for the sustainable portfolio selection problem are as follows.

Step 1: A is formed.

Table 7: The decision matrix III.

	Return	Risk	ESG
AKSEN	8	6	1
BIMAS	1	8	3
DOAS	2	2	6
ENJSA	4	7	7
MAVI	5	5	8
MPARK	3	3	2
PGSUS	6	4	4.5
THYAO	7	1	4.5

Step 2: B is formed using (1).

Table 8: The normalized decision matrix III.

	Return	Risk	ESG
AKSEN	0.222	0.167	0.028
BIMAS	0.028	0.222	0.083
DOAS	0.056	0.056	0.167
ENJSA	0.111	0.194	0.194
MAVI	0.139	0.139	0.222
MPARK	0.083	0.083	0.056
PGSUS	0.167	0.111	0.125
THYAO	0.194	0.028	0.125

Step 3: The priority values and criteria weights are found by solving (2). The weight of the return criterion equals 0.3552. The weight of the risk criterion equals 0.3306. The weight of the ESG criterion equals 0.3142.

Table 9: The priority values III.

	Weight	Rank
AKSEN	0.1428	3
BIMAS	0.1095	6
DOAS	0.0905	7
ENJSA	0.1648	2
MAVI	0.1651	1
MPARK	0.0746	8
PGSUS	0.1352	4
THYAO	0.1175	5

Step 4: The weights of AKSEN, BIMAS, DOAS, ENJSA, MAVI, MPARK, PGSUS, and THYAO are 0.1428, 0.1095, 0.0905, 0.1648, 0.1651, 0.0746, 0.1352, and 0.1175 respectively. The best alternative is MAVI, whereas the worst alternative is MPARK.

Based on Table 3, Table 6, and Table 9, it can be observed that the rankings based on different decision matrices are different. The correlation coefficient between Table 3 and Table 6 rankings equals 0.571. The correlation coefficient between Table 3 and Table 9 rankings equals 0.024. The correlation coefficient between Table 6 and Table 9 rankings equals 0.333. Furthermore, the last ranks given in these tables are different. On the other hand, there are some similarities between these rankings. For example, MAVI ranks first in all cases. This may be because it has the highest ESG score and sufficiently good predictions for the risk-return criteria.

5. Conclusions

This research investigates using an AI-based MCDM approach in sustainable portfolio selection, focusing on BIST Participation Sustainability Index stocks. The significance of this study stems from its exploration of an alternative to traditional portfolio optimization, offering investors a more holistic and innovative strategy by integrating ESG scores. The findings demonstrate that the AI-based MCDM method successfully builds optimal portfolios by including ESG scores, enabling more balanced and sustainable investment decisions than conventional approaches.

The formed portfolio changes when different criteria, expert opinions, or the MCDM method are used. Thus, this chapter does not guarantee optimal investment strategies. The portfolios formed in this chapter may not yield good real-world results. This chapter only presents an AI-based simplified perspective on sustainable portfolio selection problems. This perspective could be used or developed by the decision-makers. On the other hand, it should not be forgotten that its success highly depends on the quality of the expert knowledge.

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