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A Hybrid MCDM Approach Using the BWM and the TOPSIS for a Financial Performance-Based Evaluation of Saudi Stocks

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Abstract: This study presents a hybrid multicriteria decision-making approach for evaluating stocks in the Saudi Stock Market. The objective is to provide investors and stakeholders with a robust evaluation methodology to inform their investment decisions. With a market value of USD 2.89 trillion dollars in September 2022, the Saudi Stock Market is of significant importance for the country's economy. However, navigating the complexities of stock market performance poses investment challenges. This study employs the best–worst method and the technique for order preference by similarity to identify an ideal solution to address these challenges. Utilizing data from the Saudi Stock Market (Tadawul), this study evaluates stock performance based on financial criteria, including return on equity, return on assets, net profit margin, and asset turnover. The findings reveal valuable insights, particularly in the banking sector, which exhibited the highest net profit margin ratios among sectors. The hybrid multicriteria decision-making-based approach enhances investment decisions. This research provides a foundation for future investigations, facilitating a deeper exploration and analysis of additional aspects of the Saudi Stock Market's performance. The developed methodology and findings have implications for investors and stakeholders, aiding their investment decisions and maximizing returns.

Keywords: stocks; financial performance; evaluation; investment; MCDM; BWM; TOPSIS

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1. Introduction

Investors in the stock market are often driven by the objective of achieving high returns while minimizing risks. However, this goal becomes challenging due to various factors influencing stock market performance, such as the global economy, political events, and security concerns. To navigate these complexities, investors must consider a range of criteria to guide their decision-making process. When it comes to stock market investing, the use of multicriteria decision making (MCDM) becomes a significant challenge. Investors must evaluate and compare numerous stocks based on predetermined criteria to identify those with the most significant potential for high returns. This evaluation process involves analyzing both fundamental and stock market indicators. Fundamental indicators assess a company's financial performance, including its earnings per share, return on investment, and price-to-earnings ratio. These indicators provide insights into the company's profitability, efficiency, and valuation, which are vital considerations for investors. On the other hand, stock market indicators provide information on trading volumes and overall market risk, allowing investors to gauge market sentiment and potential volatility.

Given the complexity and diversity of the Saudi Stock Market, which encompasses more than 21 sectors and over 200 companies, selecting stocks for investment becomes an intricate task. Each sector has unique dynamics and potential opportunities, adding another layer of complexity to the decision-making process. In such situations, employing

MCDM methods becomes crucial for structuring and analyzing complex problems, enabling investors to consider multiple criteria simultaneously.

The Saudi Stock Market is of significant importance globally. With over 210 listed companies distributed across various sectors, including banks and financial services, petrochemical industries, energy, and more, the Saudi Stock Market plays a vital role in the country's economic landscape. Under the Vision 2030 initiative, the private sector's role is also increasing, with the government aiming to raise the private sector's contribution to the gross domestic product (GDP) from 40% to 65% by 2030. Given the significance of the Saudi Stock Market and the challenges associated with selecting optimal stocks for investment, there is a clear need for a hybrid model based on MCDM to guide investment decisions and maximize returns.

This study aims to address this need by utilizing MCDM methods to analyze and rank selected stocks from different sectors in the Saudi Stock Market. The objectives of this study encompass several key aspects. First, a comprehensive review of the existing literature on MCDM methods and stock market performance will be conducted. This review will provide valuable insights and establish a solid foundation for a subsequent analysis. Second, this study will identify the sectors with the most potential within the Saudi Stock Market, considering various factors such as market trends, growth prospects, and investor sentiment. Third, valuable stocks will be selected from each sector based on a thorough evaluation of their fundamental and stock market indicators. Fourth, MCDM methods will be employed to rank the selected stocks, considering the predetermined criteria and their relative importance. Finally, this study aims to rank the stocks that offer the highest return potential in the Saudi Stock Market.

This study aspires to contribute to the knowledge of MCDM methods and their application in the Saudi Stock Market. The findings will provide valuable insights and guidance for investors, enabling them to make more informed decisions and optimize their investment strategies in the dynamic and rapidly evolving Saudi Stock Market. This study offers a unique methodology tailored to the specific context of stock market evaluation, adding to the existing literature. This approach presents a fresh perspective on evaluating stock performance and assists decision-makers in making well-informed investment decisions.

The rest of this paper is structured as follows. Section 2 provides a review of the literature on key topics related to the stock market, including applications of mathematical programming, MCDM methods, and other analytical approaches used in stock market research. Section 3 outlines this study's proposed methodology, including identifying the top five sectors and stocks for each sector and criteria, determining criteria weights, and evaluating stock performance as alternatives. Section 4 presents the results of applying each stage of the methodology. Section 5 discusses the findings and results of the analysis. Finally, Section 6 summarizes the main conclusions and limitations of this study and provides recommendations for future work.

2. Literature Review

This literature review section offers a comprehensive survey of prior research relevant to the subjects examined in this paper. It is organized into four subcategories to ensure thorough coverage of key areas in the literature. Section 2.1 summarizes general studies on the stock market, highlighting the fundamental criteria deemed important for investors and presenting an overview of classification frameworks and significant findings from literature reviews in this field. Section 2.2 focuses on mathematical programming applications in the stock market, discussing utilizing a linear programming model and emphasizing the robustness of the resultant model. Section 2.3 explores various MCDM methods discussed in the literature, providing an overview of different approaches, such as preference ranking for organization method for enrichment evaluation (PROMETHEE), the best–worst method (BWM), ranking alternatives by perimeter similarity (RAPS), the technique for order preference by similarity to ideal solution (TOPSIS), and viekriterijumsko kompromisno rangiranje, a Serbian term for multicriteria optimization and compromise solution (VIKOR), which are particularly relevant to the methodology employed in this paper. Lastly, Section 2.4 examines other techniques related to the stock market, including a novel decision-making approach for stock portfolio selection and the application of a technical analysis approach. By structuring the literature review with a specific focus on stock performance measurement, the aim is to furnish pertinent background information and establish the necessity of the proposed combined methodology evaluated in this study.

2.1. General Studies on the Stock Market

Various studies shed light on different aspects of investment and financial markets. The Investment Updates Report [1] highlighted the Kingdom of Saudi Arabia's progressive shift toward a digital, cashless economy driven by the dominance of point-of-sale transactions using ATMs. The report also acknowledged the contribution of the Saudi Central Bank (SAMA)'s successful decision making to the Kingdom's exceptional financial position, which is characterized by a substantial availability of monetary reserves totaling USD 4.457 billion in foreign currencies.

In Iran, Reid et al. [2] emphasized the importance of carefully considering regulatory requirements and stakeholder expectations when choosing financial reporting approaches. Mihail et al. [3] advocated for strengthening investor relations based on their positive correlation with firm performance. Kartal [4] analyzed the effects of foreign investors on Turkish stock indices, while Katsiaryna et al. [5] demonstrated the impact of distraction events on stock return co-movement across different markets. Choiriyah et al. [6] investigated the relationship between financial performance indicators and the stock prices of banking companies on the Indonesia Stock Exchange (IDX). Their study examined variables such as the return on assets (ROA), return on equity (ROE), net profit margin (NPM), earnings per share (EPS), price-to-book ratio (P/B), and operating profit margin (OPM). The findings revealed that collectively, these indicators significantly impact stock prices. However, only the ROE and EPS demonstrated significant effects when considered individually, while the ROA, NPM, and OPM did not. Shifting the focus to the Saudi Stock Exchange, Sharif [7] (2019) examined the influence of foreign institutional investors on market dynamics. The study revealed that foreign traders play a vital role in price discovery, returning prices to their fundamental values. Finally, Wang et al. [8] proposed a novel approach to predicting financial market movements using a one-dimensional convolutional neural network (CNN) model. Their model employed customized CNN layers that scanned financial trading data over time, allowing different data types (e.g., prices and volumes) to share parameters. By extracting features automatically and avoiding biases caused by selecting technical indicators and predefined coefficients, the proposed CNN model outperformed traditional machine learning approaches regarding the average annual return and Sharpe ratio.

Vazakidis et al. [9] investigated the relationship between stock market development and economic growth in France from 1965 to 2007, using a vector error correction model (VECM) to determine how economic growth affects stock market development. Their results suggest that economic growth promotes stock market development, while interest rates have a negative effect. In their review of stock market prediction techniques, Shah et al. [10] highlighted the challenges of predicting stock prices due to the random nature of stock markets and the large number of influencing variables. Their study indicated the potential of using machine learning for longer-term market predictions. Nazir et al. [11] focused on Pakistan, showing that increasing market size and capitalization can spur stock market development and arguing that such development is significant for economic growth. Castanias [12] examined variability in stock market prices, challenging the assumption that price changes are drawn from a stationary distribution and suggesting that the arrival rate of broad economic information influences this variability. Ruzgar et al. [13] analyzed Canadian banks' stock prices during financial crises, finding that certain indexes positively influenced bank stocks during these times. Ibrahim [14] explored how stock market returns can predict actual output in Malaysia and found that stock returns have a predictive power for the economy's output in short forecasting periods. Lim and Brooks [15] surveyed the efficiency of stock markets over time, highlighting a trend toward time-varying market efficiency which suggests that the market's predictability changes over time. Fuchs-Schündeln and Funke [16] studied the impact of stock market liberalization, finding that liberalization increases investment and GDP growth, especially in the presence of strong institutional frameworks.

Sellin [17] examined the relationship between monetary policy and stock performance and discovered that the relationship between actual stock prices and inflation is significantly impacted by monetary policy. Zia-ur-Rehman et al. [18] investigated the connection between macroeconomic factors and stock market volatility in the Pakistani context. Some variables positively correlate with stock prices, whereas others have an adverse association. Together, these studies demonstrate the multitude of factors influencing the behavior of stock markets and the intricate yet vital role they play in economic development. They also highlight how crucial it is to apply cutting-edge statistical techniques in order to comprehend these processes. Every study advances our grasp of the intricate linkages between stock markets and economies, as well as our awareness of the ongoing need to monitor and modify financial and economic policies in light of these relationships. Krutika et al. [19] delved into the behavior of individual investors within the Indian stock market, examining the risk–return relationship and the influence of emotions and cognitive errors on investor decision making. The study aimed to gain insight into investors' attitudes, perceptions, and preferred sources of information, as well as the psychological factors that come into play in different market situations. The research was based on a sample of 150 equity investors.

Another study by Felix et al. [20] evaluated the efficiency of price discovery within the Nigerian Stock Exchange, focusing on the unique characteristics of stock markets in developing countries. Svitlana et al. [21] delved into the globalization of the stock market and provided a comprehensive analysis of its current state. The study considered worldwide indicators and highlighted the conditions that hinder it from functioning effectively. Sheilla et al. [22] examined the origin and development of the stock market in the United States, focusing on major exchanges such as NYSE Euronext, NASDAQ, and the Chicago Stock Exchange. The study emphasized the impact of stock market reforms implemented following the crash of 1929. Covering a period from 2000 to 2014, Boers' [23] study revealed that conflict risk is not significantly priced into individual stock returns. This analysis contributed to a more comprehensive understanding of the relationship between international conflicts and stock market dynamics.

2.2. Applications of Mathematical Programming in the Stock Market

Brito [24] addressed the EU–EV model, which is based on expected utility, entropy, and variance and is used to pick the best stocks and build portfolios. The model was employed to select stocks from the PSI 20 index (the Portuguese Stock Index) and create portfolios, with subsets of four equities proving particularly effective. Oladegio et al. [25] explained how optimization techniques were applied to generate an optimal investment in a chosen portfolio, delivering maximum returns with the fewest inputs. A redundancy constraint was established using a linear programming model, with the robustness of the resulting model to changes in input parameters determined through a sensitivity analysis. Using an optimization method, a firm with USD 15,000,000 to invest in crude oil, mortgage securities, cash crops, certificates of deposit, fixed deposits, treasury bills, and construction loans was able to create the best possible investment portfolio considering all financial risks. In 2016, Bilbao-Terol et al. [26] presented a sequential goal-programming model with fuzzy hierarchies for sustainable and responsible (SR) portfolio selection. Their model allowed SR investors to express preferences based on financial and SR objectives, offering decision support in the SR investing process. The study's implementation with real-world data from the UK SR mutual fund market showcased the model's applicability and advantages in addressing goal conflicts.

Mokhtar et al. [27] comprehensively reviewed mathematical programming models used for portfolio optimization, categorizing them as heuristic and exact solution methods and indicating that most conventional methods fall into both categories. These methods include stochastic programming and goal programming, among others. Manea et al. [28] discussed applying optimization methods in statistics, emphasizing their importance in finance. They explored the use of the simplex algorithm as a tool, highlighting its capacity to facilitate optimal strategies for investing in the stock market. Wilkens and Zhu [29] introduced a new approach to portfolio evaluation using linear programming. Their method identified efficient portfolio frontiers and benchmarks for commodity trading advisor returns, demonstrating that mathematical programming can directly influence investment strategies. Yin [30] applied interval-valued fuzzy linear programming to optimize stock portfolios, a method that allows investors to choose portfolios based on risk tolerance, illustrating that higher risks might lead to higher returns.

Mulvey [31] explored optimization models in various financial planning activities, discussing the advantages and limitations of different approaches, such as dynamic stochastic control and optimizing stochastic simulation models. Gupta et al. [32] transformed the mean-variance model using fuzzy mathematical programming optimization, empowering investors to choose between aggressive or conservative strategies while customizing their portfolios. Wang [33] examined its applications in finance, ranging from pricing assets to matching cash flows. The study showcased its evolution from linear to nonlinear programming to address increasingly complex financial scenarios. Ziemba [34] evaluated the role played by mathematical programming and stochastic methods in developing realistic portfolio theories that consider constraints and transaction costs. Thomas' work extended to dynamic models applicable to asset location in real-world scenarios. Thomas [35] considered this view on the impact of mathematical programming to be far-reaching in finance. The study emphasized its utilization in managing both assets and liabilities and its role in long-term financial planning. The interplay of techniques grounded in optimization and simulation underscores one of the cornerstones of modern financial strategies. Kaufmann and Stenseth [36] delved into the utilization of programming in mathematical education, exploring how it strengthens the foundation of financial education and indirectly enhances problem-solving skills.

These studies showcase the usefulness of mathematical programming in devising effective strategies for stock market investments. Applying these techniques in risk management, asset allocation, and return optimization enables the investor to meet market conditions and requirements. Theoretical and practical evidence supports their improved effectiveness in portfolio performance, as confirmed by research findings.

2.3. Applications of MCDM Methods in the Stock Market Context

MCDM is a subfield of operations research that addresses decision-making problems involving multiple criteria. The MCDM method aids decision-makers in selecting alternatives based on various criteria. Numerous MCDM methods are currently available for different types of decision-making problems. Kornyshova and Salinsi [37] presented a comprehensive overview of existing approaches for selecting MCDM methods. Mardani et al. [38] performed a state-of-the-art review of MCDM methods and methodologies, classifying articles based on journal name, publication year, application area, and various MCDM methods and approaches. D-Sight is an example of an MCDM method that employs the PROMETHEE method and multi-attribute utility theory. Emovon and Oghenenyerovwho [39] provided a mathematical review of MCDM methods in material selection. Recent MCDM methods and new tools proposed by scholars demonstrate continued interest in this field.

In the stock market context, Vuković et al. [40] compared hybrid MCDM methods to stock selection using modern portfolio theory, highlighting the superior risk-and-return performance of the hybrid approach. Alamoudi and Bafail [41] discussed the BWM–RAPS approach for evaluating and ranking banking sector companies on the Saudi Stock Market.

Bayda and Pamučar [42] identified the objective characteristics of MCDM methods under uncertainty, with PROMETHEE and FUCA standing out as top performers. Jing et al. [43] focused on achieving optimal stock portfolio selection by utilizing multicriteria decision-making methods to maximize returns and minimize risk in companies listed on the Tehran Stock Exchange. Peng et al. [44] proposed an MCDM method based on elimination and choice, translating reality I with Z-numbers for stock selection. Gupta et al. [45] developed a hybrid ranking technique to rank the sectoral stock indices of India's National Stock Exchange. Majumdar et al. [46] used MCDM to evaluate investment options on the Indian equity market. Mills et al. [47] presented a hybrid MCDM method for asset allocation in the Shanghai Stock Exchange. Marqués et al. [48] explored the use of MCDM methods in financial management, focusing on ranking-based models. Pattnaik et al. [49] proposed fuzzy MCDM methods for selecting the best insurance company for purchasing an online term plan. Galankashi et al. [50] (2020) integrated financial and nonfinancial criteria using the Fuzzy Analytic Network Process for portfolio selection on the Tehran Stock Exchange. Nabeeh et al. [51] combined the analytical hierarchy process (AHP) with neutrosophic techniques for decision making in IoT-based enterprises.

These studies provide valuable insights into the application of MCDM in various domains and highlight the importance of considering MCDM processes. Song and Peng [52] evaluated imbalanced classifiers in credit and bankruptcy risk prediction using an MCDM-based method that simultaneously considered multiple performance metrics. The TOPSIS method was used to rank the classifiers based on six evaluation criteria, and the combined rankings provided by TOPSIS were found to be more reasonable than individual performance criteria. Tey et al. [53] introduced the neutrosophic data analytic hierarchy process (NDAHP) for decision making under uncertainty in supply chain management, utilizing the method to evaluate the financial performance of petrochemical companies listed on the Kuala Lumpur Stock Exchange. The results, validated using ranking tests, demonstrated the accuracy of the NDAHP method. Aouni et al. [54] emphasized the importance of incorporating criteria beyond mean and variance in portfolio selection, highlighting that MCDM methods allow investors to consider a broader range of criteria and make more informed decisions. Touni et al. [55] investigated the behavioral aspects of stock selection using MCDM and the UTA-STAR method. They identified criteria (risk, return, and liquidity) that influence investors' stock investment decisions and provided insight into investors' decision-making behaviors. Makki and Alqahtani [56] captured the effect of the COVID-19 pandemic on financial performance disparities in the energy sector using a hybrid MCDM-based evaluation approach. This study contributed to understanding the impact of the pandemic on the energy sector's financial performance disparities.

Amudha et al. [57] reviewed the TOPSIS technique, a ranking technique which uses comparisons with ideal solutions. This method is particularly effective as it can balance the representation of different criteria for investment, thereby providing a realistic valuation of stock options. Toloie-Eshlaghy et al. [58] extensively reviewed MCDM methods from 1999 to 2009, operating on the premise that these methods are widely implemented in various fields, including finance. Their research categorized various MCDM methods, highlighting the extensive use of these methods in complex decision-making. Baydaş et al. [59] evaluated the financial performance of companies using several MCDM techniques. Their assessment revealed that methods with low standard deviations in results and strong interdependence with real-life financial performance, such as PROMETHEE and FUCA, could be rated superior. Poklepović et al. [60] combined and modified two MCDM methods, producing divergent results in stock selection by applying different MCDM methods, thereby increasing reliability in stock valuation in the Croatian capital market.

Ho et al. [61] introduced the first decision-making model, representing a preference-based novel MCDM model for portfolio selection aligned with the capital asset pricing model (CAPM). The model addressed multiple investment criteria and their interrelationships, providing a holistic portfolio management solution. Lee et al. [62] employed MCDM techniques to assess stocks, utilizing the dividend and growth rate-oriented Gordon model.

They devised a method of factoring in complex variables and their interactions, which could help investors understand why some stocks perform better than others. Baydaş et al. [63] proposed objective criteria for a fair comparison of MCDM methods in financial performance evaluation. They found that hybrid weighting techniques are more effective across all periods compared to other methods. In a more recent study, Işık et al. [64] used MCDM methods to assess the performance of food and beverage companies listed on the Istanbul Stock Exchange, capturing significant differences in company performances by amalgamating various MCDM techniques.

Sotoudeh-Anvari [65] conducted a review of MCDM applications during the era of COVID-19, showcasing the method's flexibility in addressing complex, multifaceted problems. Together, these studies indicate the flexibility and practicality of MCDM methods in financial decision making. MCDM models provide a framework for analyzing different investment alternatives in detail, considering even the most complex and, in some cases, conflicting criteria. This indicates that MCDM is an important tool for financial analysts and investors. Swagata et al. [66] explored the use of a novel hybrid MCDM technique combining GRA, AHP, and TOPSIS for ranking stocks in the Indian IT sector based on various performance indicators.

Mohamed et al. [67] conducted a pivotal evaluation in 2020, offering valuable insights for manufacturing industries aiming to achieve investment goals, particularly in revenue enhancement. The study evaluated the top 10 steel companies in Egypt based on specified financial ratios, determining company ranking and demonstrating consistent results. Mohammad et al. [68] proposed a hybrid MCDM technique that evaluates and ranks banks based on the criteria of the balanced scorecard (BSC) and corporate social responsibility (CSR) views. Abdolhamid et al. [69] evaluated Iranian automotive companies using a hybrid approach based on accounting and economic value measures, using the fuzzy analytical hierarchy process (FAHP) to determine criteria weights and rank the companies. Meysam et al.'s [70] evaluation model was developed for the Iranian petrochemical industry using the fuzzy AHP and FTOPSIS methods. Yitong et al. [71] used the Monte Carlo (MC) model in the financial field to price financial options and multi-period income guarantees, aiding in risk analysis, management, financial analysis, and marketing. The MC simulation model provides a probability distribution of uncertain objects via probability simulations and the statistical testing of random variable functions. This provides significant application value in financial derivative pricing and risk analysis. Seyed et al. [72] proposed a new hybrid approach comprising a simplified group BWM and multicriteria sorting to categorize options while considering decision-maker constraints. The proposed approach was employed in an actual case study of stock portfolio selection on the Tehran Stock Exchange.

2.4. Other Techniques Related to the Stock Market

Narang et al.'s [72] study introduced a novel decision-making approach for stock portfolio selection. The approach integrated a fuzzy combined compromise solution (CoCoSo) with the Heronian mean operator to distribute capital among selected stocks, aiming to achieve profitable returns with lower risk. By combining these methods, the authors proposed a new decision-making model for stock selection and utilized particle swarm optimization to construct portfolios based on the rankings obtained. The results demonstrated satisfactory returns compared to previous studies, suggesting the effectiveness of their approach for stock portfolio selection. Paula and Iquiapaza [73] discussed investment fund selection in the fixed income and stock segments, utilizing performance indicators such as the Sharpe ratio and factor model alpha efficiency measured through data envelopment analysis (DEA). Their study aimed to enhance knowledge of pension fund investment decisions and promote confidence in using the Sharpe ratio as a technique for fund selection. The study analyzed data from 369 funds from 2013 to 2018, considering multiple temporal windows for portfolio selection.

Aljifri [74] comprehensively analyzed the Saudi Stock Price Index (TASI) and its relationship with domestic macroeconomic variables, international variables, and global oil prices. The study employed a multiple-equation time series analysis and considered the impact of local and global financial crisis events. The findings indicated a long-run relationship between the variables, with a positive equilibrium relation between TASI and the S&P 500 and oil prices, but a negative relationship with the money supply. Manoharan and Rajesh Mamilla [75] measured the occurrence and efficiency of various bullish reversal candlestick patterns in predicting stock market trends. Their study focused on 17 stocks on India's leading market benchmark index, NIFTY 50, over the course of 16 years. Data mining techniques with back-testing methodology were employed to identify the most efficient candlestick patterns, including bullish engulfing, piercing line, and morning star.

Dayag and Trinidad [76] explored the use of price–earnings (P/E) ratios to assess the investment potential of universal banks in the Philippines. The study analyzed the P/E ratios of 10 leading banks and their relationships to overall stock market performance, focusing on the ROE, the price–book value (PBV) ratio, and the Philippine Stock Exchange (PSE) index as significant variables. Huang and Liu [77] investigated the application of a multifactor model to understand correlations between various factors and stock returns on the Chinese market. Their hybrid approach combined traditional statistical analysis and machine learning techniques to enhance the accuracy of predicting stock returns.

Noor and Rosyid [78] examined the impact of financial ratios, specifically the loan deposit ratio (LDR) and the ROE, on the share price performance of PT Bank Danamon Indonesia. A regression analysis was used to explore the relationship between the ratios and stock prices, with significant influences found for the capital adequacy ratio (CAR) and LDR. Zhou et al. [79] proposed an approach for stock portfolio selection in a fuzzy environment, incorporating varying risk attitudes, confidence levels, and value at risk (VaR) into the decision-making process. Their study provided a framework for investors to navigate stock selection while considering individual risk preferences. Paiva et al. [80] introduced a decision-making model for day trading investments on the stock market, combining machine learning methods with portfolio selection strategies. Their integrated approach incorporated technical indicators as features in machine learning algorithms for forecasting stock returns, optimizing portfolio allocation using mean-variance optimization, and employing a genetic algorithm. This methodology aimed to provide a comprehensive approach to decision making in financial trading.

Rajput et al. [81] devised various techniques to predict stock movements by analyzing sentiments from social media using data mining techniques. All this leads to the conclusion that stock prediction is an extremely complex task requiring the consideration of diverse factors, which may enhance the accuracy and efficiency of how forecasts are presented. Ou et al. [82] assessed the efficacy of predicting the movement of the Hang Seng Index using 10 different data mining techniques. Their research found that among the tested models, the support vector machine (SVM) and least-squares support vector machine (LS-SVM) demonstrated outstanding performance, suggesting they hold the greatest potential for enhancing prediction capability in this domain.

A. E. Khedr et al. [83] focused on using a sentiment analysis of financial news data combined with historical price data to predict trends. Their model included news sentiment, which significantly improved the accuracy of its predictions and illustrated the importance of including qualitative data in the forecasting model. As Atsalakis [84] noted, there are a plethora of such traditional forecasting methods, among which the ARIMA model is capable of capturing the nonlinear dynamics of stock markets and offers significant predictive power. However, applying these methods may seem somewhat tedious. While complicated, these methods are of paramount importance for comprehending and effectively predicting market behavior. Sharma et al. [85] articulated various methods applied in predicting stock market trends, elaborating the shift from conventional models to state-of-the-art machine learning and deep learning methodologies. Their study highlights the need for continuous evolution in prediction methods to adapt to the volatile nature of stock markets.

In their review, Rouf et al. [86] underscored significant strides made in machine learning prediction, which has seen substantial advancements in accuracy through leveraging innovative algorithms and ensemble methods. This illustrates how dynamic characteristics adapt over time to new technological advancements in stock market prediction. According to Kumbure et al.'s [87] literature reviews, different types of variables and techniques have been applied in machine learning for stock forecasting. Additionally, a bibliometric analysis indicates emerging trends in the utilization of sophisticated tools for understanding and predicting market trends.

Gandhmal et al. [88] summarized the various techniques used for predicting stock markets, including fuzzy classifiers and neural networks, outlining their advantages and disadvantages. This effort served to highlight gaps in the current research landscape and proposed avenues for future research aimed at enhancing prediction accuracy. In another study, Jabin [89] used artificial neural networks (ANNs) for short-term stock market predictions, identifying a trend of high prediction accuracy. This achievement speaks volumes about the potential of ANNs for capturing complex market relationships. Usmani et al. [90] conducted a comparative study using different machine learning techniques to predict the performance of the Karachi Stock Exchange. They found that external factors, such as oil and foreign exchange rates, are critical, and a unifactorial approach cannot provide accurate predictions. Bustos et al. [91] conducted a critical examination of the neuro-fuzzy system in forecasting stock trends, calling into question the efficient market hypothesis. Based on their research, they concluded that combining computational intelligence with aspects of financial analysis offers numerous benefits in prediction.

In summary, these studies present a diverse and evolving range of techniques aimed at understanding and predicting stock market trends. The combined methodology examined in this paper offers various insights and avenues for enhancing prediction accuracy, which is crucial for investment strategies in rapidly changing financial environments.

After conducting a literature review, several key factors influenced the decision to use the BWM and TOPSIS in this study. The literature highlighted the importance of considering multiple criteria and decision making under uncertainty in the stock market context. MCDM methods such as the BWM and TOPSIS have been widely used in stock market research due to their ability to manage multiple criteria and provide rankings or evaluations of alternatives.

Additionally, previous studies have demonstrated the effectiveness of the BWM and TOPSIS in various domains, including stock market analysis and portfolio selection. For example, Alamoudi and Bafail [41] discussed applying the BWM–RAPS approach to evaluate and rank banking sector companies on the Saudi Stock Market. Furthermore, Makki and Alqahtani [56] evaluated financial performance disparities in the Saudi energy sector before, during, and after COVID-19 using a hybrid MCDM approach, highlighting impacts and providing insights for decision-makers. These studies provided evidence of the suitability of the BWM and TOPSIS for evaluating and ranking stocks based on financial indicators.

The selection of financial indicators as criteria for evaluating stock performance was driven by previous research findings highlighting the correlation between financial performance indicators and stock prices. Choiriyah et al.'s [6] study on banking companies on the Indonesia Stock Exchange (IDX) found that indicators such as the ROA, ROE, NPM, EPS, P/B, and OPM significantly impact stock prices. This suggests that financial indicators can provide valuable insights into the performance of stocks and their potential for generating returns.

The objective of this study is to evaluate the performance of stocks based on financial indicators using the BWM and TOPSIS methods. The details of the materials and methods employed in this research are provided in the next section.

3. Materials and Methods

The structure of the suggested methodology for measuring and ranking stocks on the Saudi Stock Market is shown in Figure 1. The proposed method consists of three consecutive stages. In the first stage, an evaluation was conducted to evaluate the top five sectors of the stock market by market cap. The number of listed companies varies across sectors, and the selection is based on the top 25% of stocks in each sector by market cap. The second stage employed the BWM to calculate the weights of the criteria collected from the expert subject matter. In the third stage, the chosen stocks were ranked using the TOPSIS approach. This involved identifying an alternative closest to the ideal solution and farthest from the negative ideal solution in a multidimensional computing space. These rankings were based on the overall performance of the stocks, as determined by the weighted criteria calculated in the previous stage.

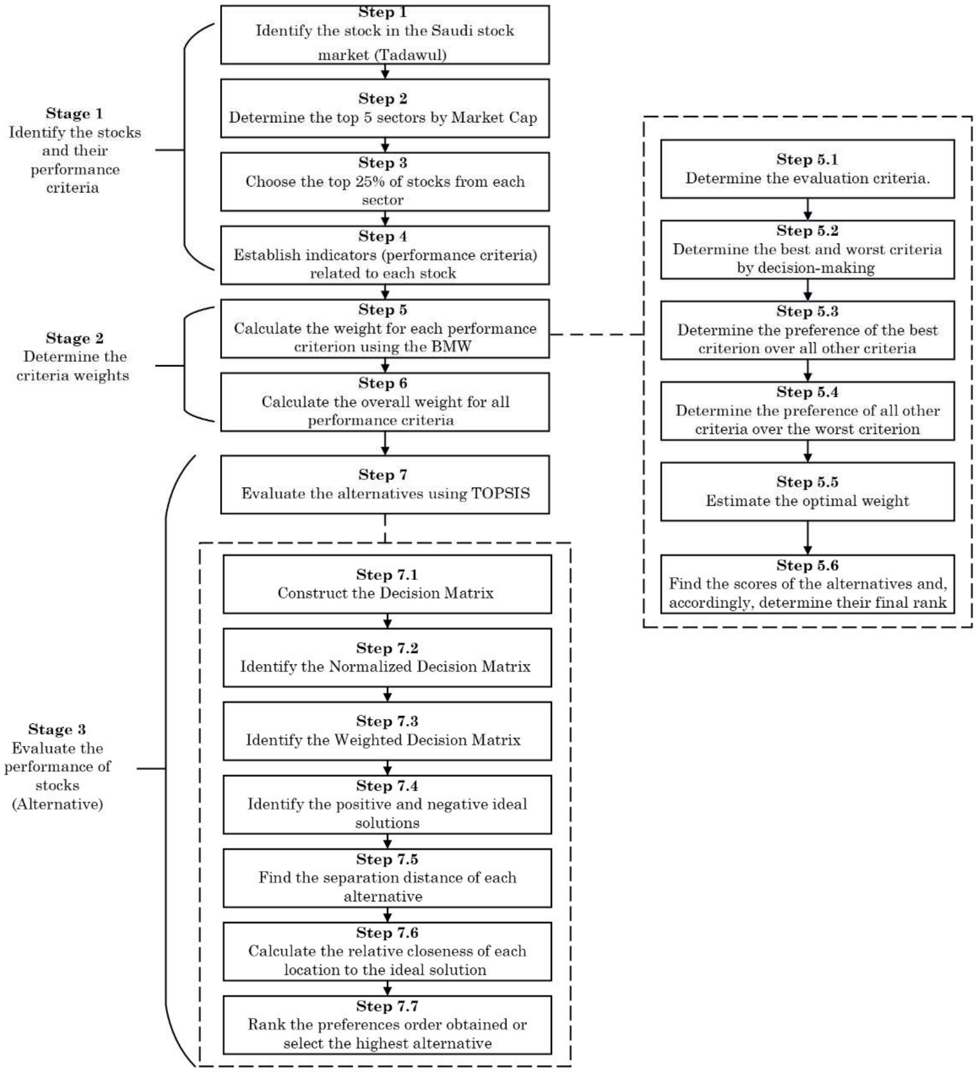

Figure 1. The proposed framework for evaluating the stocks.

The proposed methodology enhances the understanding of the research question by providing a clear and structured approach to evaluating the stock market. It contributes by providing methodological clarity, considering multiple criteria, integrating subjective and objective factors, offering decision support, and providing a novel application in the stock market context. It ensures transparency and replicability by offering a step-by-step process. Considering multiple criteria enables a comprehensive evaluation of stock market performance, including fundamental and stock market indicators.

The integration of subjective and objective factors captures qualitative and quantitative aspects. The BWM allows decision-makers to express preferences while TOPSIS incorporates objective data, resulting in a balanced evaluation that enhances decision making. The methodology provides actionable insights for investors through stock rankings and the identification of top-performing sectors. This guidance supports investment strategies and portfolio management. It introduces a novel application of the hybrid MCDM approach in the context of the stock market. Adopting the BWM and TOPSIS brings a unique methodology tailored to stock market evaluation, expanding the knowledge base and offering new research opportunities.

3.1. Identifying Stocks and their Performance Criteria

Step 1 involves selecting stocks from the Saudi Stock Market, which encompasses over 210 listed stocks across 21 sectors.

Step 2 involves selecting the sectors likely to yield optimal returns. This selection process is based on market capitalization, which reflects the size and value of a company. The top five sectors with the highest degree of market capitalization in the Saudi Stock Market are the energy sector, banks, materials, utilities, and telecommunications services.

Step 3 involves evaluating listed companies across sectors. The top 25% of stocks in each sector are selected based on their market capitalization, so the number of companies meeting the selection criteria will differ from sector to sector.

Once the stocks have been identified, Step 4 focuses on establishing criteria for evaluating each stock. Investors rely on well-defined criteria to assess stocks and make informed investment decisions. These criteria encompass various factors, such as profitability, market conditions, and validation like asset turnover (ATO). By considering these diverse criteria, investors can comprehensively understand a company's potential and reduce the risks associated with impulsive or uninformed investment choices.

A comprehensive analysis of numerous papers published on the subject emphasizes the significance of stock selection criteria in the investment process. The criteria are categorized into three main groups: profitability, market conditions, and validation. Each category comprises sub-criteria, which are outlined in Table 1.

Table 1. Criteria for evaluating stocks.

Criteria	Sub-Criteria *
Profitability	ROE ROA Net profit margin
Market	EPS P/E P/B
Validation	ATO

* return on equity (ROE), return on assets (ROA), earnings per share (EPS), price–earnings (P/E) ratio, price-to-book (P/B) ratio, and asset turnover (ATO).

3.2. Determining Criteria Weights

Step 5 focuses on assigning weights to the stock performance criteria. The BWM is the appropriate method for MCDM problems. A survey was conducted involving 10 finance experts who were actively involved in investment consulting in the Saudi Stock Market. The purpose was to gather insights on how these experts assessed the importance of each performance criterion. The participants had varying levels of experience and education, which can be found in Table A1 in Appendix A. The data utilized in this study were obtained from the main market website, which is the official website of the Saudi Market Exchange (Tadawul) [92]. According to Munim et al. [93], the following steps explain the calculation of weight criteria using the BWM.

Step 5.1: Formulate the problem; the decision-maker determines the evaluation criteria.

Step 5.2: Identify the best and worst criteria. The decision-maker determines the best (most important) criterion and the worst (least important) criterion for use in the comparison process to determine the vectors used in finding the criteria weights.

Step 5.3: Determine the preference for the best criterion over all other criteria. The decision-maker ranks the best criterion's importance over all other criteria using a 1–9 scale, where 1 indicates the same importance of the two criteria and 9 indicates the extreme importance of one criterion over another. The resulting best-to-others vector will be

$$A_B = (a_{b1},\ a_{b2}, \ldots,\ a_{bn}), \tag{1}$$

where a_{bj} expresses the preference for the best criterion b over criterion j, and the decision-maker identifies the best criterion (b).

Step 5.4: Determine the preference for all other criteria over the worst criterion.

Step 5.3: The decision-maker ranks the importance of all other criteria over the worst criterion using a scale from 1 to 9. This results in the other worst vector.

$$A_W = (a_{1w},\ a_{2w}, \ldots,\ a_{nw}), \tag{2}$$

where a_{jw} expresses the preference for criterion (j) over the worst criterion (w); the decision-maker identifies the least important criterion (w).

Step 5.5: Estimate the optimal weight. This step aims to minimize the absolute differences:

$$\left(\left|w_b - a_{bj}w_j\right|, \left|w_j - a_{wj}w_w\right|\right) \tag{3}$$

For all j to reach the optimal criteria weights, observe the following linear programming model:

$$min\delta^L \tag{4}$$

Subject to

$$\left|w_b - a_{bj}w_j\right| \leq \delta^L \text{ for all } j, \tag{5}$$

$$\left|w_j - a_{wj}w_w\right| \leq \delta^L \text{ for all } j, \tag{6}$$

$$\sum_j w_j = 1 \tag{7}$$

$w_j \geq 0$, for all j.

a_{bj}: represents the preference for the best criterion b over criterion j.

a_{jw}: represents the preference for the criterion j over the worst criterion w.

w_b: indicates the optimal weights of the best criteria.

w_w: indicates the optimal weights of the worst criteria.

w_j: indicates the optimal weights of the other criteria.

δ^L: indicates the consistency ratio of the comparison procedure in the BWM.

Step 5.6 Find the scores of alternatives. To find the final rank of the alternatives, decision-makers rank the alternatives using a 1–9 score, where 1 indicates that the alternative was not implemented at all, and 9 indicates that it was the most implemented alternative. Then, normalize these scored values by dividing each value by the maximum value in its column. After that, multiply the normalized values by their respective weights. Finally, taking the row-wise averages gives us the final ranking of the alternatives. The following equation can represent this step:

$$F_i = \sum_{j=1}^{n} w_j\ \ x_{ij}^{norm}, \tag{8}$$

F_i: the final score of the alternative i.

x_{ij}^{norm}: the normalized score of criterion j under alternative i.

Step 6: In this step, calculate the overall weight of each performance criterion.

3.3. Evaluating the Stocks' Performance (Alternatives)

The last stage evaluates the stocks' performance by ranking the alternatives from best to least. The TOPSIS method is based on identifying an alternative closest to the ideal solution and furthest to the negative ideal solution in a multidimensional computing space. According to [94] (Kumar et al., 2020), the steps of the TOPSIS method can be given as follows:

Step 7.1: The first stage includes establishing a decision matrix (DM).

$$DM = \begin{array}{c} \\ C_1 \\ C_2 \\ \cdot \\ C_m \end{array} \begin{bmatrix} L_1 & L_1 & \ldots & L_n \\ X_{11} & X_{12} & \ldots & X_{1n} \\ X_{21} & X_{22} & \ldots & X_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ X_{m1} & X_{m2} & \ldots & X_{mn} \end{bmatrix} \text{ or } DM = \left[X_{ij}\right], \tag{9}$$

where j (j =1, 2, 3,. . . , n) is the criteria index, n denotes the number of potential sites available in the DM, and i refers to the alternative index (i = 1, 2, 3,. . ., m). The elements L_1, L_2,. . .., L_n denote different criteria, while the elements (C_1, C_2,. . ., C_m) refer to alternative locations.

Step 7.2: Calculating the normalized decision matrix (NDM); the NDM represents the relative performance of design alternatives.

$$NDM = R_i = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2} \tag{10}$$

Step 7.3: Calculating the weighted decision matrix (WDM); the WDM is constructed by multiplying each element of the column of (NDM) by its respective weight.

$$WDM = V = V_{ij} \; = W_j \times R_{ij} \tag{11}$$

Step 7.4: Identifying the positive ideal solution A^+ and negative ideal solution A^-, which are determined by the weighted decision matrix (WDM) defined in (11) above via Equations (12) and (13) by using the following formulas:

$$\begin{gathered} A^+ = \{\, v_1^+ \;, v_2^+ \,, v_3^+, \ldots, \, v_n^+ \}, \\ \text{Where } V_j^+ = \{ (max\, v_{ij} | j \in J^+), \, (min\, v_{ij} | j \in J^-) \}. \end{gathered} \tag{12}$$

$$\begin{gathered} A^- = \{\, v_1^- \;, v_2^- \,, v_3^-, \ldots, \, v_n^- \}, \\ \text{Where } V_j^- = \{ (min\, v_{ij} | j \in J^+), (max\, v_{ij} | j \in J^-) \}. \end{gathered} \tag{13}$$

$$\left(J^+ = 1, 2,\ 3,\ \ldots,\ n\right) J^+ \text{ for the benefit criteria.} \tag{14}$$

$$\left(J^- = 1, 2, 3,\ \ldots,\ n\right) J^- \text{ for the cost criteria.} \tag{15}$$

where J^+ and J^- in Equations (12) and (13) are associated with the beneficial and non-beneficial attributes, respectively.

Step 7.5: Find the separation distance of each alternative from the ideal and non-ideal solutions.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2}, i = 1, 2, 3, \ldots, m. \tag{16}$$

$$S_i^- = \sqrt{\sum_{j=1}^{\mathrm{n}} \left(v_{ij} - v_j^-\right)^2}, i = 1, 2, 3, \ldots, m. \tag{17}$$

where i = criterion index and j = alternative index.

Step 7.6: Calculate the relative closeness C_i of each location to the ideal solution and the relative closeness of the alternative A_j concerning it.

$$C_i = S_i^- \,/\, \left(S_i^+ + S_i^-\right), \tag{18}$$

where $0 \leq C_i \leq 1$; i=1, 2, . . ., m.

Step 7.7: Rank the preference order obtained or select the highest alternative. Different alternatives can be arranged in descending order by the C_i values from the previous equation.

The hypothesis of this study is that the above-described methodology and its three stages, utilizing the collected data, can be applied to achieve this study's objective of evaluating the performance of stocks based on financial indicators. The three stages are concerned with identifying the stocks and their performance criteria, determining the criteria weights, and evaluating their performance. This, in turn, results in a list of ranked stocks based on the weighted criteria. The following section describes the application of the proposed method and its results.

4. Results

This section is structured into three subsections which provide the outcomes of each stage in the proposed methodology. Section 4.1 discusses Stage 1, which involves identifying stocks and their performance criteria. Section 4.2 elaborates the findings of Stage 2, which entails determining the weights of the criteria using the BWM approach. Finally, Section 4.3 outlines the assessment and ranking of stock performance as alternatives in Stage 3, employing the TOPSIS method.

4.1. Stage 1: Identify the Stocks and their Performance Criteria

Step 1 involves selecting the most suitable stocks (alternatives) from a wide range of options after evaluating the Saudi Stock Market, which comprises 21 distinct sectors and over 210 listed stocks.

Step 2 involves sector selection, a critical component of achieving optimal returns. The selection process involves identifying and choosing the top five sectors in the Saudi Stock Market based on their market capitalization in US dollars. Focusing on the sectors with the highest market capitalization enhances investment potential and maximizes the chances of achieving favorable outcomes. The top five sectors by market capitalization in the Saudi Stock Market are energy, banks, materials, utilities, and telecommunications services. Table 2 provides additional details about these sectors, including their market capitalization.

Table 2. The market value of sectors in the Saudi Stock Market (2022).

Sector	Market Value (USD)
Energy	1,896,280,856,333.33
Banks	252,086,109,763.23
Materials	184,257,016,737.73
Utilities	60,392,126,915.87
Telecommunication Services	58,459,002,881.47

In Step 3, the evaluation of listed companies differs between sectors and is determined by selecting the top 25% of stocks in each sector based on their market capitalization. Consequently, the number of listed companies that meet the selection criteria will vary depending on the sector. Table 3 shows each sector and the companies listed.

Table 3. The selected companies for each sector.

Sector	Alternative
Energy	A1 A2
Materials	A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13
Banks	A14 A15 A16
Telecommunication Services	A17
Utilities	A18 A19

Step 4 involves identifying the criteria for evaluating each stock. Investors rely on well-defined criteria to evaluate stocks and make informed investment decisions. In an extensive analysis of a significant body of papers published on related topics, it was consistently observed that stock selection criteria were consistently mentioned as a crucial aspect of the investment process. The criteria were divided into three main categories: profitability, market conditions, and validation. Each category included sub-criteria, as shown in Table 1. Following these criteria enables investors to make more informed decisions, minimize risk exposure, and enhance their chances of achieving investment objectives.

4.2. Stage 2: Determining Criteria Weights

Step 5 involves weighting the stock performance criteria. This step is undertaken through the BWM by examining the preference for the best criterion over other criteria and obtaining the preference for all criteria over the worst criterion. The overall weight for the seven sub-criteria is determined using a survey conducted with 10 finance experts who actively participate in investment consulting within the Saudi Stock Market context. The survey's primary objective was to gather insights regarding the experts' evaluations of the importance of each performance criterion. The criterion weights are calculated using the BWM, and the summation of the weights should equal 1, as shown in Table 4.

Table 4. Estimating the optimal weights for the sub-criteria.

Sub-Criteria *	**ROE**	**ROA**	**Net Profit Margin**	**EPS**	**P/E**	**P/B**	**ATO**	**Total**
Weights	0.165	0.11	0.29	0.11	0.165	0.05	0.11	1

* return on equity (ROE), return on assets (ROA), earnings per share (EPS), price–earnings (P/E) ratio, price-to-book (P/B), and asset turnover (ATO).

4.3. Stage 3: Evaluating the Stocks' Performance (Alternatives)

Step 6, the final step, involves evaluating the performance of the selected stocks by ranking the alternatives from best to least. The TOPSIS method identifies an alternative closest to the ideal solution and farthest from the negative ideal solution in a multidimensional computing space. This method considers the overall performance of the alternatives based on the weighted criteria calculated in the previous stage. By incorporating these methodologies, this study ensures a comprehensive evaluation of the alternatives and their performance based on the specified criteria. Table 5 shows the results of ranking the alternatives using the TOPSIS method.

Table 5. Calculating performance score.

Alternative	ROE	ROA	Net Profit Margin	EPS	P/E	P/B	ATO	Rank
A8	0.0922	0.0731	0.1096	0.0866	0.0090	0.0145	0.0337	1
A13	0.0749	0.0451	0.0386	0.0481	0.0103	0.0135	0.0591	2
A3	0.0330	0.0044	0.1338	0.0176	0.0227	0.0131	0.0017	3
A1	0.0690	0.0472	0.0546	0.0101	0.0153	0.0186	0.0437	4
A9	0.0414	0.0302	0.0727	0.0204	0.0089	0.0064	0.0210	5
A4	0.0215	0.0039	0.1230	0.0129	0.0161	0.0061	0.0016	6
A5	0.0241	0.0038	0.1182	0.0096	0.0176	0.0074	0.0016	7
A16	0.0335	0.0240	0.0582	0.0107	0.0254	0.0149	0.0208	8
A7	0.0320	0.0164	0.0480	0.0104	0.0222	0.0124	0.0174	9
A19	0.0308	0.0175	0.0374	0.0100	0.0194	0.0105	0.0236	10
A18	0.0113	0.0062	0.0435	0.0149	0.0082	0.0016	0.0072	11
A2	−0.0141	−0.0033	−0.0041	−0.0027	−0.0207	0.0051	0.0410	12
A15	0.0104	0.0053	0.0356	0.0041	0.0161	0.0029	0.0076	13
A6	0.0146	0.0104	0.0173	0.0226	0.0210	0.0054	0.0305	14
A11	−0.0155	−0.0087	−0.0231	−0.0034	−0.0214	0.0058	0.0190	15
A17	0.0148	0.0062	0.0605	0.0087	0.0935	0.0243	0.0051	16
A14	0.0157	0.0070	0.0207	0.0047	0.0485	0.0133	0.0172	17
A10	0.0057	0.0049	0.0122	0.0030	0.0732	0.0073	0.0203	18
A12	0.0050	0.0049	0.0000	0.0015	0.0775	0.0068	0.0000	19

The results of applying the proposed hybrid MCDM approach using the BWM and TOPSIS attained this study's objective. The results in the first stage of the proposed approach helped identify the top five sectors in the Saudi Stock Market and their top 25% of stocks based on their market capitalization. It also helped determine the main financial performance criteria and their relevant sub-criteria, based on which the evaluation was conducted. Based on expert input, the BWM determined the sub-criteria weights in the second stage. In the third stage, the TOPSIS method was used to evaluate the stocks' performance and revealed their rankings. Therefore, based on the achieved results, the hypothesis is approved. The following section provides a discussion of the achieved results.

5. Discussion

In the past five years, the Saudi Stock Market has undergone significant transformation, with the top five sectors in market capitalization demonstrating notable growth compared to other sectors. This growth has made these sectors attractive to investors seeking to assess and analyze the constituent companies within each sector. Various criteria were considered to evaluate and rank the value of these companies. An extensive review of published papers emphasized the importance of stock selection criteria in the investment process. These criteria can be broadly categorized into three main groups: profitability, market conditions, and validation. To gain insights from experts in the field, seven academics from the Faculty of Economics, Engineering, and Business who specialized in finance and were actively involved in investment consulting in the Saudi Stock Market were consulted. The findings revealed that profitability was deemed the most critical criterion, carrying a weight of 56.5%. Market conditions and validation were weighted at 32.5% and 11%, respectively.

Hybrid MCDM methods were utilized in this study to evaluate seven criteria for the Saudi Stock Market. The aim was to establish a comprehensive performance evaluation framework by employing the BWM to assign weights to the criteria and use the TOPSIS method to rank the alternatives. According to the TOPSIS results, A8 emerged as the top-ranking company. When considering the weighted criteria for profitability, A8 showcased exceptional performance in terms of its ROE, ROA, and NPM, with returns of 47%, 37%, and 52%, respectively. Next in the ranking were A13 and A3. A13 exhibited strong performance by the end of 2023, with a 39% ROE and an 18.6% NPM. A3 boasted the highest NPM at 64.5%, but its lower ROA of 2.2% affected its overall ranking.

In contrast, A12 ranked the lowest in both ROE (2.6%) and ROA (2.5%). Notably, the bank sector displayed the highest NPM ratios compared to other sectors, with A3, A4, and A5 recording percentages of 64.5%, 59%, and 57%, respectively. Similarities and differences can be observed by comparing the findings of this study with previous research in the field. Like other studies, this research underscores the importance of financial indicators such as the ROE, ROA, NPM, EPS, P/E, P/B, and ATO in evaluating stock performance. However, it is essential to note that some disparities may arise due to variations in sample size, period, the inclusion of other criteria, or methodological differences.

Our evaluation of stocks on the Saudi Stock Market using an MCDM approach underscores the importance of providing robust policy implications that can guide stakeholders, policymakers, and regulatory bodies in making informed decisions. Our study's primary objective was to offer investors a reliable evaluation methodology for informed investment decisions, and we acknowledge the significance of extending its policy implications.

One key policy implication of our research is the identification of sectors and stocks with strong financial performance. By considering multiple financial criteria such as the ROE, ROA, NPM, and ATO, we identified sectors that exhibit high return potential. Policymakers can utilize this information to develop targeted policies and initiatives to foster growth and investment in these sectors. Such interventions can contribute to the country's overall economic development by creating a favorable environment for these sectors to thrive.

Moreover, our findings shed light on the performance of the bank sector, which displayed the highest NPM ratios compared to other sectors. Policymakers and regulators can utilize this insight to enhance the banking industry's stability and efficiency. This may involve implementing regulatory measures to ensure sound financial practices and mitigate risks. Additionally, policymakers can consider introducing incentives and initiatives that encourage further investments in the banking sector, fostering its growth and contribution to the economy.

This study aligns with the Vision 2030 initiative, which aims to promote economic diversification and increase the private sector's contribution to the GDP. By identifying and evaluating stocks with high return potential, our research provides valuable guidance for policymakers and investors seeking to strengthen the private sector. Policymakers can leverage our findings to develop targeted strategies and policies that facilitate investment, entrepreneurship, and innovation in sectors with significant growth prospects. This can contribute to realizing the Vision 2030 goals by fostering a dynamic and competitive private sector.

Similarly, applying the TOPSIS method to rank alternatives based on the established criteria weights provided a robust evaluation framework. The effectiveness of TOPSIS in decision making, including stock market analysis, is supported by the work of Hwang and Yoon [95], in which incorporating actual market data into the analysis improved the validity and practical applicability of the results. This is consistent with the findings of previous studies, such as [96–98], which underscored the importance of using actual data to enhance the reliability of decision-making methods in stock market analysis.

6. Conclusions

This research study aimed to evaluate stocks in the Saudi Stock Market using a hybrid MCDM approach and provide investors and stakeholders with a robust evaluation methodology for making informed investment decisions. The primary objective was to enhance the reliability and accuracy of stock evaluation while reducing bias.

This study employed the BWM and TOPSIS to evaluate stock performance based on various financial criteria, including the ROE, ROA, NPM, and ATO.

This study's findings revealed that the banking sector displayed the highest NPM ratios compared to other sectors. By implementing hybrid MCDM-based methods, this research provides a foundation for a deeper exploration and analysis of additional aspects of the Saudi Stock Market's performance.

This study adds twofold value to scientific research. First, it contributes to the existing literature by applying a hybrid MCDM approach to evaluating stocks on the Saudi Stock Market. Second, the combination of the BWM and TOPSIS provides a comprehensive evaluation methodology that considers multiple criteria simultaneously, enabling investors to make more informed decisions.

Secondly, this study offers a systematic approach to stock evaluation and selection in the Saudi Stock Market. It utilizes financial criteria and MCDM techniques, which can assist investors in maximizing their returns.

In conclusion, this research study contributes to the knowledge of MCDM methods and their application in evaluating Saudi stocks. The findings and insights gained from this study can guide investors in their decision-making processes and optimize their strategies for investing in the dynamic and rapidly evolving Saudi Stock Market.

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Appendix A

Table A1. Stock market expert profiles.

Expert Number	Qualification	Sector	Years of Experience *
1	Ph.D.	Capital Market Authority	16
2	Master's degree	Public Investment Fund	15
3	Ph.D.	Saudi Exchange	12

Table A1. *Cont.*

Expert Number	Qualification	Sector	Years of Experience *
4	Bachelor's degree	Ministry of Investment	10
5	Ph.D.	Public Investment Fund	11
6	Master's degree	Capital Market Institutions	13
7	Bachelor's degree	Ministry of Investment	9
8	Master's degree	Saudi Exchange	9
9	Bachelor's degree	Capital Market Institutions	8
10	Master's degree	The Financial Academy	7

* Years of experience specific to stock market-related roles only.

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