

Article

Evaluating Saudi Banks' Financial Performance Using an Entropy–TOPSIS Framework

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Abstract

As Saudi Arabia accelerates its Vision 2030 economic diversification, the domestic banking sector serves as the critical engine for capital deployment. However, evaluating these institutions is complicated by conflicting performance indicators, where high profitability is often offset by elevated market valuation multiples. This study applies an objective, established multi-criteria decision-making (MCDM) framework—combining Shannon's Entropy for objective weighting with TOPSIS for ranking—to evaluate ten major banks listed on the Saudi Stock Exchange (Tadawul), tracked by the Tadawul All Share Index (TASI), over the 2021–2025 period. The contribution is contextual and empirical rather than methodological: the systematic application of established objective MCDM methods to the Saudi banking sector during the pivotal Vision 2030 window, with an investor-oriented criterion set. Comparative validation was executed using the CRITIC weighting algorithm and the VIKOR ranking method, complemented by a four-dimensional sensitivity analysis (Weight Perturbation, Leave-One-Criterion-Out, Alternative Normalization, and Equal-Weight scenarios). Spearman correlation coefficients (>0.86) confirm that the framework produces empirically stable rankings resistant to methodological perturbation, providing policymakers and investors with a data-driven decision-support tool for the Saudi banking sector under Vision 2030.

Keywords: MCDM; TOPSIS; entropy; VIKOR; CRITIC; Saudi banking sector; TASI; equity valuation



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1. Introduction

The architectural framework of global finance relies intrinsically upon the resilience, liquidity, and operational efficiency of the commercial banking sector. Across global equity markets, banking stocks operate as the fundamental basis of macroeconomic stability and capital formation (Levine, 2005). When sovereign stock markets flourish, it is almost exclusively because the underlying financial institutions are successfully executing their primary mandate: matching surplus capital with productive corporate debt. Unlike technology or consumer discretionary equities, which often derive their market valuations from speculative future growth, banking equities are inextricably linked to the tangible reality of the present economy. They are sensitive barometers of monetary policy, reacting intimately to shifting interest rate cycles, inflation metrics, and sovereign credit ratings (Bekaert & Harvey, 2014).

As global capital markets become increasingly digitized and interconnected, banking stocks have transcended their historical roles as mere dividend-yielding safe havens. Today,

institutional investors view commercial banking equities as strategic assets that reflect a nation's capacity for systemic growth (Demirgüç-Kunt & Maksimovic, 1998). In developed economies, the banking sector is largely saturated, characterized by fierce competition over fractional margins. However, in emerging and transitional markets, the banking sector is the primary conduit through which rapid national modernization is funded. In these high-growth environments, evaluating the fundamental health of banking equities requires a sophisticated understanding of how significant inflows of foreign direct investment (FDI), state-sponsored infrastructure lending, and rapid retail expansion impact a bank's balance sheet (Stiglitz, 2000).

This global paradigm finds a distinct application within the Kingdom of Saudi Arabia. The Saudi state is currently orchestrating a significant macroeconomic transition under the auspices of Vision 2030, a comprehensive sovereign mandate designed to permanently sever the nation's historical dependency on petrochemical revenues (Government of Saudi Arabia, 2016). To manifest this reality, the Kingdom requires trillions of dollars in mobilized capital to fund large-scale infrastructure projects—such as NEOM, the Red Sea Project, and Qiddiya—alongside the rapid expansion of domestic logistics, tourism, and non-oil manufacturing (Louzis et al., 2012). While the Public Investment Fund (PIF) serves as the primary sovereign funding entity for these initiatives, the domestic commercial banking sector remains the primary channel for liquidity in the broader context. Directed by the stringent, strictly conservative regulatory frameworks of the Saudi Central Bank (SAMA), Saudi banks are currently navigating an era of rapid expansion, balancing the substantial opportunities of state-backed corporate lending with the inherent risks of rapid credit growth (Al-Khouri, 2011).

The primary financial ecosystem for this structural economic transition is through TASI (Bin Amin & Rehman, 2022). Over the past decade, TASI has evolved from a regionally isolated exchange into a globally integrated exchange, officially gaining inclusion in the MSCI Emerging Markets Index and attracting record levels of foreign institutional capital (Alotaibi & Mishra, 2017). Within TASI, the financial sector is the primary constituent, dominating the market capitalization of the index. Consequently, the performance of Saudi banking stocks dictates the trajectory of the entire exchange (Maghyreh et al., 2015). Yet, as the macroeconomic landscape evolves and these banks post robust operational metrics, a critical and an inherently complex question arises for both retail and institutional investors: how do we systematically and accurately measure the relative financial performance of these publicly traded banks?

Traditionally, equity analysts and portfolio managers have relied on isolated fundamental metrics to judge a bank's viability. Metrics such as Return on Equity (ROE), Return on Assets (ROA), and Net Profit Margin have long been the industry standard for measuring internal profitability (Pasiouras & Kosmidou, 2007). However, modern corporate equity valuation is rarely one-dimensional. An analysis restricted to pure profitability is fundamentally incomplete. For instance, a Saudi bank might post elevated net margins due to high-volume retail lending, but simultaneously be trading at an unsustainable market premium, reflected by significantly inflated Price-to-Earnings (P/E) or Price-to-Book (P/B) ratios. In such a scenario, the stock may represent a suboptimal allocation of capital despite the underlying company's operational success (Fama & French, 2015).

When these single-dimensional metrics conflict—when a highly profitable bank is too expensive, or a cheap bank suffers from poor liquidity—human analysts are inherently forced to make subjective compromises. An analyst must arbitrarily decide whether current profitability outweighs market overvaluation, inevitably introducing analyst bias and subjective market sentiment into the evaluation process (Kahneman & Tversky, 1979).

In volatile or rapidly expanding markets, this subjective guesswork frequently leads to inefficient portfolio allocations.

Multi-criteria decision-making (MCDM) provides a systematic resolution to this analytical dilemma. By utilizing advanced mathematical frameworks to process multiple, heavily conflicting criteria simultaneously, systematically balancing the mathematical benefits of profitability against the explicit costs of market valuation, MCDM models act as objective evaluation tools (Zavadskas et al., 2016). They mitigate subjective market sentiment and qualitative brand perceptions, reducing complex financial realities into quantifiable geometric distances and objective utility scores.

Despite the growing body of MCDM applications in banking, three distinct gaps characterize the existing literature on Saudi banking performance evaluation. First, most recent Saudi-focused MCDM studies apply static, single-year rankings that fail to capture the intertemporal dynamics of institutional performance across the Vision 2030 transformation window. Second, existing studies rarely integrate market valuation criteria (P/E, P/B, P/S) with profitability metrics, producing rankings informative for regulators but analytically incomplete for institutional and retail investors. Third, methodological validation in prior Saudi banking MCDM research typically relies on a single sensitivity dimension, leaving robustness against alternative weighting schemes, normalization techniques, and criterion sets largely untested.

This study addresses these gaps directly. While the integration of Entropy, TOPSIS, CRITIC, and VIKOR is a well established methodology, its specific application to the Saudi banking sector during the Vision 2030 macroeconomic transition provides a distinct empirical contribution. Accordingly, the primary objective of this research is to deploy this objective MCDM framework to evaluate the ten major banking institutions listed on the Saudi Stock Exchange over a five-year window (2021–2025). By systematically balancing core operational profitability against market valuation multiples, this study provides an investor-oriented decision-support mechanism suitable for a transitional economy.

2. Literature Review

The intersection of financial performance evaluation and operational research has experienced substantial development over the past two decades, largely driven by the increasing computational complexity of global equity markets (Yalcin et al., 2012). Investors and sovereign regulators alike have recognized that traditional, single-ratio fundamental analysis is structurally inadequate for capturing the multidimensional reality of modern banking (Stojić et al., 2018). Consequently, the application of multi-criteria decision-making (MCDM) algorithms to equity valuation represents a notable methodological advancement in quantitative finance.

2.1. MCDM Applications in Structurally Comparable Emerging Markets

To contextualize the necessity of these advanced algorithmic models, one must examine their deployment across global equity markets that share similar macroeconomic architectures. Emerging and rapidly transitioning economies serve as a primary context for applying financial MCDM frameworks, as these algorithms excel at overcoming subjective analyst biases to measure fundamental institutional performance (Radovanović et al., 2020). To accurately contextualize the Saudi banking sector, contemporary financial literature frequently applies MCDM frameworks to structurally robust, highly liquid economies that mirror the Saudi Arabian landscape. For instance, evaluating commercial banking performance within the broader Gulf Cooperation Council (GCC) requires specialized mathematical arbitration. Because GCC nations share similar US Dollar-pegged currencies and experience substantial inflows of resource-backed liquidity, researchers utilize

frameworks like the Best–Worst Method (BWM) and Ranking Alternatives by Perimeter Similarity (RAPS) approach to strip away regional liquidity biases, ensuring that banks in the Saudi stock market are ranked purely on operational efficiency and true financial indicators (Alamoudi & Bafail, 2022).

This reliance on objective mathematical frameworks is highly relevant to expanding BRICS economies that are facing rapid technological and structural transformations. In China, where the commercial banking sector is highly competitive and rapidly innovating amidst the financial technology (fintech) revolution—analogous to the rapid modernization required by Saudi Arabia’s Vision 2030—MCDM algorithms are deployed to isolate operational efficiency from nominal size. By applying hybrid multi-criteria evaluations (such as DEMATEL and VIKOR), researchers can identify the banks that maintain genuine fundamental health and sustainable competitive advantages over those merely riding macroeconomic trends (Sharma & Kumar, 2019).

Similarly, studies evaluating banking equities in other rapidly scaling emerging markets, such as India and Brazil, have consistently demonstrated that MCDM models offer significant advantages over purely subjective analyst ratings. In India, multi-criteria frameworks successfully separate true operational excellence from the speculative market enthusiasm generated by rapid economic growth (Duarte Júnior, 2018). In Brazil, fuzzy MCDM models, such as the TODIM method, have been successfully utilized to accurately evaluate and benchmark commercial bank valuations, proving that these methodologies can identify optimal financial stability amidst complex, high-growth market dynamics (Kou et al., 2021). Ultimately, the broad academic consensus within global financial literature is that multi-criteria risk analysis is a highly adaptable methodological tool (Saaty, 1980). In stable, heavily capitalized economies like Saudi Arabia, these algorithms are crucial for mitigating the influence of market sentiment and identifying institutions that are fundamentally optimizing their financial fundamentals.

2.2. The Evolution of Weighting Mechanisms: Subjective vs. Objective

Despite the widespread adoption of MCDM in finance, the methodology has evolved significantly to address inherent mathematical vulnerabilities. The early MCDM literature was heavily reliant on subjective weighting techniques, most notably Thomas Saaty’s Analytic Hierarchy Process (AHP) (Saaty, 1980). While revolutionary in its ability to structure complex decisions through hierarchical trees, AHP requires exhaustive pairwise comparisons by human experts. In the context of dynamic stock markets, this reliance on expert elicitation makes the model highly vulnerable to human fatigue, recency bias, and the subjective preferences of analysts (Saaty, 1980).

To completely counteract these cognitive biases, contemporary quantitative researchers have pivoted toward strictly data-driven, objective weighting mechanisms. Shannon’s Entropy (Shannon, 1948), a concept originally developed for information theory and signal processing, has emerged as a prominent analytical tool in corporate finance. Entropy operates on a robust mathematical foundation: if all companies perform identically in a specific metric, that metric offers no discriminatory power and is therefore ineffective for ranking them. Consequently, Entropy assigns heavier mathematical weights to criteria demonstrating high systemic variance, allowing the raw data itself to dictate what is currently important in the market (Keshavarz-Ghorabae et al., 2021).

Alongside Entropy, the CRITIC method (Diakoulaki et al., 1995) has gained significant recognition in the contemporary literature. Highlighted frequently in journals such as *Symmetry* and *Mathematics*, CRITIC is regarded as a robust alternative to Entropy because it accounts for both data variance and the inter-criteria correlation (e.g., the natural mathematical overlap between ROA and ROE), ensuring that highly correlated metrics do not

unfairly monopolize the final decision weight (Diakoulaki et al., 1995; Puška et al., 2021; Žižović et al., 2020).

2.3. Distance and Compromise Ranking Algorithms

For the actual ranking of financial alternatives, Hwang and Yoon's TOPSIS (Hwang & Yoon, 1981) remains the widely accepted benchmark (Zakeri & Chatterjee, 2021). Its foundational premise—locating the specific bank that is mathematically closest to a theoretical Positive Ideal Solution while being simultaneously furthest from the Negative Ideal Solution—is intuitively aligned with the core tenets of value investing (Zakeri & Chatterjee, 2021). Contemporary studies frequently pair TOPSIS with Entropy to evaluate a diverse array of financial ecosystems, ranging from supply chain resilience (Pamucar et al., 2020) to the sustainability parameters of Islamic banking (Opricovic & Tzeng, 2004).

However, in the modern era of operational research, presenting a solitary TOPSIS ranking is no longer considered academically sufficient. Modern researchers demand rigorous stress testing. Therefore, scholars consistently employ the VIKOR method (Opricovic & Tzeng, 2004) as a robust comparative tool. While TOPSIS measures strict geometric distance, VIKOR introduces a mechanism of compromise—maximizing collective group utility while minimizing individual regret—providing a vital mathematical counter-perspective to demonstrate that a ranking hierarchy is structurally stable (Ecer, 2021), with similar comparative validations conducted in emerging-market stock exchanges (Baydaş & Elma, 2021).

2.4. The Saudi Context and the Case for an Objective, Investor-Oriented Ranking

As Saudi Arabia's TASI has grown significantly in scale and international integration, the literature focusing on the exchange has naturally expanded. Within the broader finance literature, Data Envelopment Analysis (DEA) has historically served as the dominant methodology for evaluating banking performance. Extensive research has utilized DEA to measure the technical, pure technical, and scale efficiencies of both conventional and Islamic banking institutions across the GCC and emerging economies (Al-Muharrami, 2008; Johnes et al., 2014; Ullah et al., 2023).

However, while DEA is well suited to internal operational benchmarking—typically comparing physical inputs like employee costs or branch networks to outputs like total loans or net income—it is structurally insufficient for the specific problem addressed in this study. DEA is fundamentally designed to measure production efficiency, not investor equity value. It cannot mathematically accommodate conflicting market valuation multipliers, such as Price-to-Earnings (P/E), Price-to-Book (P/B), and Dividend Yield, which are critical for determining if a highly profitable bank is actually trading at an unsustainable market premium.

Because DEA cannot resolve the conflict between internal profitability and external market valuation, researchers evaluating stock performance often turn to multi-criteria decision-making (MCDM) methods, such as the BWM or fuzzy logic frameworks. While these methods successfully allow for the integration of conflicting financial criteria, they introduce a critical flaw: subjectivity. Standard MCDM models rely heavily on expert elicitation to determine the weights of the criteria. In dynamic, heavily capitalized stock exchanges like TASI, this reliance on human judgment makes the evaluation particularly vulnerable to analyst fatigue, recency bias, and emotional market sentiment.

Therefore, because DEA is not designed to capture equity-market valuation metrics, and traditional subjective MCDM approaches carry a risk of analyst bias, the objective Entropy–TOPSIS framework offers a highly suitable alternative. While the algorithms used in this study—Entropy, TOPSIS, CRITIC, and VIKOR—are well established in decision

science, their application to the Saudi banking sector remains limited. Accordingly, the contribution of this study lies not in methodological invention, but in the systematic, multi-year empirical application of these tools to deliver a transparent, investor-oriented ranking directly relevant to the Vision 2030 economic transformation.

3. Methodology and Raw Data

3.1. Data Acquisition and Criteria Definition

This empirical study examines the ten primary banking institutions listed on Tasi over a five-year horizon spanning 2021 to 2025. The criteria adopted in this study are drawn from the investor-oriented perspective on banking performance evaluation, focusing on indicators that inform portfolio allocation, equity valuation, and shareholder return expectations. These indicators—profitability metrics (ROE, ROA, NPM), market valuation multiples (P/E, P/B, P/S), and shareholder distributions (Dividend Yield, EPS)—are the standard indicators employed by institutional investors, sell-side analysts, and asset managers in emerging-market banking research. Bank-specific regulatory indicators serving regulatory supervision purposes fall outside this analysis.

The eight financial criteria adopted in this study are summarized in Table 1. The raw decision matrices for all five years are presented in Tables A1–A5 (Appendix A).

Table 1. Financial criterion.

Code	Category	Financial Criterion	Optimization Type	Literature Base
C1	Profitability	Return on Equity (ROE)	Benefit (+)	(Diakoulaki et al., 1995; Keshavarz-Ghorabae et al., 2021)
C2	Profitability	Return on Assets (ROA)	Benefit (+)	(Diakoulaki et al., 1995; Keshavarz-Ghorabae et al., 2021)
C3	Profitability	Net Profit Margin	Benefit (+)	(Diakoulaki et al., 1995; Žižović et al., 2020)
C4	Market Valuation	Price-to-Sales (P/S)	Cost (−)	(Puška et al., 2021)
C5	Yield	Dividend Yield	Benefit (+)	(Keshavarz-Ghorabae et al., 2021; Puška et al., 2021)
C6	Market Valuation	Price-to-Earnings (P/E)	Cost (−)	(Puška et al., 2021; Žižović et al., 2020)
C7	Market Valuation	Price-to-Book (P/B)	Cost (−)	(Puška et al., 2021; Žižović et al., 2020)
C8	Profitability	Earnings Per Share (EPS)	Benefit (+)	(Žižović et al., 2020)

Financial data for the 2021–2024 fiscal years reflect fully audited annual consolidated statements published on the Saudi Exchange (Tadawul) issuer platform, prepared in accordance with International Financial Reporting Standards (IFRS) as endorsed in the Kingdom of Saudi Arabia and standards issued by the Saudi Organization for Chartered and Professional Accountants (SOCPA).

For the 2025 fiscal year, the analysis reflects the most recent available data as of the data collection cutoff date of 15 February 2026. At this cutoff point, the majority of Saudi banks had not yet released their fully audited FY2025 annual reports. Accordingly, the 2025 figures represent interim data extracted from MarketScreener (marketscreener.com), which aggregates trailing-twelve-months (TTM) figures compiled from Q4 2025 preliminary disclosures published on Tadawul and each bank’s Investor Relations releases. This reflects the practical constraint of empirical analysis conducted at the frontier of the observation window.

All ratios were computed using standardized formulas consistent with CFA Institute conventions: ROE = Net Income / Average Total Equity; ROA = Net Income / Average Total Assets; NPM = Net Income / Total Operating Income; P/E = Fiscal Year-End Closing Price / Basic EPS; P/B = Fiscal Year-End Closing Price / Book Value per Share; P/S = Market Capitalization / Total Operating Income; Dividend Yield = Total Annual Dividends per Share / Fiscal Year-End Closing Price; EPS = Net Income Attributable to Ordinary Shareholders / Weighted Average Shares Outstanding. Equity-market variables reflect closing

prices on 31 December of each fiscal year (or the closest preceding trading day for interim 2025 observations). The methodological approach builds on recent comparative studies of bank performance under macroeconomic stress (Akbulut et al., 2024).

The selection of these specific criteria is heavily supported by the established financial MCDM literature, drawing directly from models used in global emerging-market banking analyses (Duarte Júnior, 2018; Sharma & Kumar, 2019). Profitability indicators—specifically Return on Equity (ROE), Return on Assets (ROA), and Net Profit Margin—are universally utilized to capture core operational efficiency (Alamoudi & Bafail, 2022; Pasiouras & Kosmidou, 2007). Conversely, market multipliers such as Price-to-Earnings (P/E) and Price-to-Book (P/B) are standard algorithmic mechanisms for measuring equity premiums and associated investment costs (Fama & French, 2015; Song et al., 2024). Table 1 details the selected criteria alongside their assigned codes, their optimization direction, and their supporting literature base.

Because the natural logarithm of zero is undefined, the zero-yield values (C5) for the selected banks would normally cause the Shannon Entropy calculation to fail. To resolve this, a negligibly small constant was added to these specific data points during normalization. This adjustment allows the formula to compute correctly without distorting the underlying dataset.

3.2. The Entropy Weighting Algorithm

To mathematically extract the importance of each financial ratio without human interference, Shannon's Entropy was applied (Shannon, 1948). The raw decision matrix is first normalized to ensure comparability:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$$

where x_{ij} represents the raw performance value of i -th bank with respect to j -th performance ratio where $i = 1, 2, 3 \dots m$ and $j = 1, 2, 3 \dots n$.

The specific entropy value (E_j) is then computed, utilizing a standardizing constant k :

$$E_j = -k \sum_{i=1}^m P_{ij} \ln (P_{ij})$$

The objective weight (W_j) is derived from the degree of divergence ($d_j = 1 - E_j$):

$$W_j = \frac{d_j}{\sum_{j=1}^m d_j}$$

3.3. The TOPSIS Ranking Mechanism

Following weight extraction, TOPSIS was utilized to establish the definitive hierarchy (Hwang & Yoon, 1981).

The Vectorial Normalization is calculated:

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}}, i = 1, \dots, m; j = 1, \dots, n$$

The weighted normalized value is calculated:

$$v_{ij} = w_j \cdot r_{ij}, i = 1, \dots, m; j = 1, \dots, n$$

The Euclidean distance from each bank to the Positive Ideal Solution (S_i^+) is calculated:

$$S_i^+ = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^+)^2}$$

Subsequently, the distance to the Negative Ideal Solution (S_i^-) is computed:

$$S_i^- = \sqrt{\sum_{j=1}^n (V_{ij} - V_j^-)^2}$$

The absolute performance is represented by the closeness coefficient (C_i), which dictates the final ranking:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

4. Empirical Results and Discussion

4.1. Entropy Weighting Results (2021–2025)

Shannon's Entropy, originally formulated as a measure of informational uncertainty in communication systems (Shannon, 1948), has since been rigorously adapted as an objective weighting mechanism in financial MCDM frameworks, precisely because its mathematical logic transfers directly: criteria exhibiting high variance across alternatives carry greater discriminatory power and are therefore assigned higher weights. Applying this principle to the present dataset requires a year-by-year analytical structure rather than a pooled five-year average. Collapsing the data into a single static model would obscure the dynamic shifts in market prioritization that characterize the Saudi banking sector during the post-pandemic recovery window of 2021–2025, effectively averaging out the very variance that Entropy is designed to capture. Analyzing the longitudinal dataset annually therefore serves a dual purpose: it reveals the stable underlying behavioral patterns of the eight financial criteria within a SAMA-regulated, currency-stable banking environment, while simultaneously preserving the sensitivity of the model to year-specific structural shifts in dividend policy, valuation multiples, and earnings performance. The resulting weight distributions, presented in Tables 2–6, consistently reflect the competitive homogeneity of core profitability metrics alongside the high divergence of shareholder return indicators. The subsections that follow systematically examine these patterns, beginning with the dominant criterion before addressing secondary drivers and their collective implications for the dynamic ranking model.

Table 2. Entropy weights of financial criterion (2021).

Financial Criterion	Entropy (E)	Divergence (d)	Weight (W)	Weight (%)
C1	0.960	0.040	0.132	13.25%
C2	0.981	0.019	0.064	6.40%
C3	0.994	0.006	0.020	1.99%
C4	0.981	0.019	0.064	6.42%
C5	0.898	0.102	0.341	34.10%
C6	0.993	0.007	0.024	2.39%
C7	0.928	0.072	0.241	24.12%
C8	0.966	0.034	0.113	11.34%

Table 3. Entropy weights of financial criterion (2022).

Financial Criterion	Entropy (E)	Divergence (d)	Weight (W)	Weight (%)
C1	0.980	0.020	0.103	10.32%
C2	0.989	0.011	0.055	5.53%
C3	0.995	0.005	0.026	2.64%
C4	0.988	0.012	0.060	5.98%
C5	0.931	0.069	0.358	35.81%
C6	0.994	0.006	0.031	3.13%
C7	0.966	0.034	0.178	17.77%
C8	0.964	0.036	0.188	18.81%

Table 4. Entropy weights of financial criterion (2023).

Financial Criterion	Entropy (E)	Divergence (d)	Weight (W)	Weight (%)
C1	0.989	0.011	0.048	4.80%
C2	0.988	0.012	0.050	5.04%
C3	0.994	0.006	0.024	2.39%
C4	0.974	0.026	0.108	10.85%
C5	0.920	0.080	0.338	33.77%
C6	0.982	0.018	0.076	7.64%
C7	0.952	0.048	0.200	20.05%
C8	0.963	0.037	0.155	15.46%

Table 5. Entropy weights of financial criterion (2024).

Financial Criterion	Entropy (E)	Divergence (d)	Weight (W)	Weight (%)
C1	0.987	0.013	0.055	5.46%
C2	0.987	0.013	0.054	5.38%
C3	0.995	0.005	0.020	2.04%
C4	0.974	0.026	0.109	10.93%
C5	0.929	0.071	0.296	29.56%
C6	0.976	0.024	0.100	10.00%
C7	0.947	0.053	0.224	22.40%
C8	0.966	0.034	0.142	14.24%

Table 6. Entropy weights of financial criterion (2025).

Financial Criterion	Entropy (E)	Divergence (d)	Weight (W)	Weight (%)
C1	0.989	0.011	0.037	3.68%
C2	0.989	0.011	0.035	3.55%
C3	0.996	0.004	0.015	1.46%
C4	0.976	0.024	0.078	7.80%
C5	0.838	0.162	0.532	53.23%
C6	0.987	0.013	0.041	4.12%
C7	0.954	0.046	0.152	15.23%
C8	0.967	0.033	0.109	10.93%

4.1.1. The Dominance of Dividend Yield

A primary observation across the five-year period is that the Dividend Yield indicator has the highest weight, ranging from 29.56% in 2024 to a peak of 53.23% in 2025—comparing to other criterion across the time-window selected. This demonstrates that Dividend Yield possessed the highest degree of divergence each year. Financially, this suggests that dividend distribution policies vary considerably among the evaluated banks, with some institutions aggressively distributing cash to shareholders while others retain earnings for capital requirements or expansion.

This concentrated weighting warrants critical interpretation. The elevated Dividend Yield weight raises the question of whether it reflects genuine differences in financial

performance or primarily heterogeneity in payout policy across institutions. A balanced reading suggests that both dimensions contribute. On the performance side, sustained high dividend yields require consistent earnings generation, prudent capital allocation, and sufficient regulatory buffers—each a meaningful indicator of underlying financial health. On the policy side, dividend distributions also reflect board-level strategic choices between shareholder returns and retained earnings for growth investment, which are not purely performance-driven signals. Consequently, the Entropy-derived rankings should be interpreted as capturing a composite signal—reflecting both operational performance and distribution strategy—rather than performance alone.

4.1.2. Secondary Drivers: Valuation Multiples and Earnings

Following Dividend Yield, Price-to-Book (PB) and Earnings Per Share (EPS) consistently emerged as the next most heavily weighted criteria.

PB maintained a strong weighting across the timeframe, averaging approximately 19.8% (ranging from 15.23% in 2025 to 24.12% in 2021). This high divergence points to significant disparities in how the market values the net assets of different institutions.

EPS also showed substantial weight, maintaining a relatively stable range between 10.93% and 18.81%.

4.1.3. The Uniformity of Profitability Margins

In contrast, the criteria related to core operational profitability—specifically Net Profit Margin, Return on Assets (ROA), and to a slightly lesser extent, Return on Equity (ROE)—consistently generated the highest entropy values, resulting in the lowest overall weights. Net Profit Margin was repeatedly the least impactful criterion, carrying a weight of merely 1.46% to 2.64% across the five years. ROA similarly hovered around 3.5% to 6.4%. While these metrics are fundamentally vital to financial health, the EWM algorithm assigns them minimal weight because the values are largely homogenous across the banks. This implies a competitive and strictly regulated environment where the core profitability margins of the banks are tightly clustered. Because these metrics do not show significant variance, they offer minimal leverage for ranking one institution over another.

4.1.4. Implications for the Dynamic Ranking Model

The multi-year EWM results confirm that the subsequent performance rankings are heavily influenced by shareholder return metrics (Dividend Yield) and market valuation differences (PB), rather than core operational margins (Net Profit Margin, ROA). By applying these distinct weights to separate TOPSIS evaluations for each respective year, the resulting model dynamically captures annual market shifts. While utilizing five-year averages is a common technique to minimize the impact of short-term economic volatility, maintaining separate annual models provides a much more granular view of how market sentiment and dividend policies immediately alter institutional rankings over time. This methodology ensures that the final evaluation precisely reflects the structural evolution of the banking sector from 2021 to 2025.

4.2. TOPSIS Closeness Coefficients and Longitudinal Performance Rankings (2021–2025)

After applying the dynamic entropy weights to the decision matrices, the TOPSIS framework calculated each bank's geometric distance to both the ideal and anti-ideal financial states. The resulting closeness coefficient serves as the final arbiter of performance: a score closer to 1.0 represents a bank that is maximizing returns while minimizing financial costs (Hwang & Yoon, 1981).

4.2.1. Dynamic Market Leadership and Volatility

This volatility is most apparent at the very top of the rankings. Market leadership was highly competitive, with no single bank managing to hold the number one spot for more than two consecutive years. Take Saudi Awwal Bank (SAB), for example. It showed a significant upward trend, climbing from seventh place in 2021 to secure the highest rank in the sector in 2023 and 2024 ($C_i = 0.934$). However, SAB experienced a notable decline in 2025, dropping to eighth. This decrease clearly illustrates the model's sensitivity to market shifts: as the earlier entropy analysis demonstrated, 2025 was a year heavily defined by dividend payouts. Banks that did not proportionally adjust their dividend strategies relative to their peers experienced significant rank reductions.

On the other hand, the Arab National Bank (ANB) and Saudi National Bank (SNB) demonstrated substantial structural resilience. ANB concluded the 2025 period in the top position, largely by maximizing its distance from negative financial traits ($S^- = 0.248$) while SNB demonstrated its fundamental stability by remaining in the top three for four straight years.

4.2.2. Consistent Stability in the Mid-Tier

In contrast to the high rank volatility at the top, mid-tier banks like Alriyadh and Banque Saudi Fransi (BSF) demonstrated consistent stability. Alriyadh comfortably held the third or fourth position from 2022 onwards, while BSF steadily improved, eventually capitalizing on the 2025 market shifts to take second place overall. This kind of consistency points to rigorously disciplined, conservative financial governance, insulating these institutions from the higher rank volatility observed elsewhere in the sector.

4.2.3. Al Rajhi Bank Ranking Analysis

One of the most notable findings from the TOPSIS analysis is the consistently low ranking of Al Rajhi Bank within this framework. Even though the institution is a dominant player in the Saudi market with substantial net profits and a strong Return on Equity (ROE), it remained, under this study's specific criteria, near the bottom of the list between seventh and tenth place across all five years studied. This outcome highlights the analytical strength of the model rather than a judgment on the bank's underlying financial health. It is because within TOPSIS calculations, valuation metrics such as Price-to-Earnings (P/E) and Price-to-Book (P/B) ratios are treated as cost criteria. Banks trading at higher valuation multiples receive a lower closeness score, all else equal. Al Rajhi Bank's elevated P/E and P/B ratios during the period studied place it at a disadvantage on these specific dimensions, even as it scores strongly on profitability-based criteria. This result should be interpreted as conditional on the selected criteria set and their cost/benefit classification, rather than as a claim about the bank's fundamental or intrinsic value, or as any form of investment guidance. Within the bounds of this framework, the finding illustrates how the Entropy–TOPSIS approach jointly weighs profitability and valuation, rather than relying on profitability metrics alone.

4.2.4. Banking Performance Trends (2021–2025)

Ultimately, tracking these rankings from 2021 to 2025 demonstrates a key finding: absolute size and gross profit do not automatically translate to superior performance when evaluated through a rigorous multi-criteria lens. Institutions like ANB and SNB consistently outperformed highly capitalized peers by maintaining a healthier equilibrium between operational profits, generous shareholder payouts, and reasonable market valuations. By running separate models for each year rather than relying on a single static average, this study captures the market dynamics, demonstrating how quickly institutional dominance

can shift when fundamental financial priorities change. Table 7 consolidates these year-by-year findings into a longitudinal overview, summarizing the ranking trajectory of each bank across the entire 2021–2025 horizon. It must be explicitly stated that these rankings are strictly conditional on the selected financial criteria set and the mathematical assumptions of the Entropy–TOPSIS framework, and should not be construed as prescriptive investment advice.

Table 7. Longitudinal Entropy–TOPSIS rankings of Saudi banks (2021–2025).

Bank	2021 Rank	2022 Rank	2023 Rank	2024 Rank	2025 Rank
Arab National Bank (ANB)	2	6	2	3	1
Banque Saudi Fransi (BSF)	4	4	6	5	2
Saudi National Bank (SNB)	8	1	3	2	3
Alriyadh	1	3	4	4	4
Bank Aljazira	5	9	9	9	5
Bank Albilad	9	10	10	10	6
Alrajhi	10	8	7	8	7
SAB	7	2	1	1	8
Saudi Investment Bank (SAIB)	3	5	5	6	9
Alinma Bank	6	7	8	7	10

5. Methodological Validation: Overview of CRITIC and VIKOR Frameworks

To verify the structural stability and robustness of the primary performance rankings, a methodological validation was conducted using an alternative multi-criteria decision-making (MCDM) framework. Specifically, the Criteria Importance Through Inter-criteria Correlation (CRITIC) method was utilized to cross-verify the objective weights, while the VIKOR method was applied to validate the final ranking of the alternatives.

5.1. Objective Weighting via the CRITIC Method

The CRITIC methodology calculates the objective weight by measuring two distinct concepts:

- Contrast Intensity: Represented by the standard deviation of each criterion. A higher standard deviation indicates greater informational value.
- Conflicting Character: Measured by the Pearson correlation coefficient between the j -th and k -th performance indicators, calculated across all evaluated Saudi banks.

The total amount of information contained within a criterion is expressed mathematically as:

$$C_j = \sigma_j \sum_{k=1}^m (1 - r_{jk})$$

The final objective weight is then determined by normalizing this information measure across all criteria. By utilizing CRITIC as a comparative baseline, this study ensures that the criteria weights are validated not just by internal divergence, but also by their broader correlational impact on the financial matrix.

5.2. Compromise Ranking via the VIKOR Method

VIKOR introduces a multi-criteria ranking index based on the measure of closeness to the ideal point, focusing on maximum group utility and minimum individual regret of the opponent (Opricovic, 1998). The method calculates three primary values for each alternative:

- Utility Measure: Represents the maximum group utility (the sum of the distances to the best values).

- **Regret Measure:** Represents the maximum individual regret (the maximum distance to the best value among all criteria).
- **VIKOR Index:** A synthesized compromise score that balances and using a predefined weight for the strategy of maximum group utility.

The alternative with the lowest value is proposed as the optimal compromise solution. Because VIKOR strictly penalizes severe underperformance in any single highly weighted financial indicator, it serves as an excellent, conservative tool against the geometric distance calculations utilized in TOPSIS.

5.3. Overall Spearman Rank Correlation

A Spearman rank correlation was conducted across all fifty data points (10 banks $\times$ 5 years). The baseline Entropy–TOPSIS framework yielded a high 0.966 correlation with Entropy–VIKOR, and an 0.869 correlation with CRITIC–TOPSIS (Baydaş & Elma, 2021). These metrics comfortably exceed the standard threshold for statistical reliability, demonstrating that the highest-ranked banks maintain their positions regardless of the geometric logic applied.

5.4. Comparative Analysis and Methodological Robustness (2021–2025)

An essential component of this study involves validating the primary Entropy–TOPSIS rankings against alternative multi-criteria algorithms (Entropy–VIKOR and CRITIC–TOPSIS). As illustrated in Tables 8–12, the most prominent finding is the high degree of structural consensus among the models. Across the entire five-year observation period, the models rarely disagreed by more than two rank positions for any given bank.

Table 8. Comparative ranking across distinct MCDM algorithms (2021).

Banks	Entropy–TOPSIS	Entropy–VIKOR	CRITIC–TOPSIS
Alriyadh	1	1	1
Arab National Bank (ANB)	2	3	4
The Saudi Investment Bank	3	4	5
Banque Saudi Fransi (BSF)	4	2	3
Bank Aljazira	5	6	7
Alinma Bank	6	5	6
SAB	7	8	8
SNB	8	7	2
Bank Albilad	9	10	10
Alrajhi	10	9	9

Table 9. Comparative ranking across distinct MCDM algorithms (2022).

Bank	Entropy–TOPSIS	Entropy–VIKOR	CRITIC–TOPSIS
SNB	1	1	1
SAB	2	2	5
Alriyadh	3	3	2
Banque Saudi Fransi (BSF)	4	4	4
The Saudi Investment Bank	5	5	3
Arab National Bank (ANB)	6	6	7
Alinma Bank	7	8	9
Alrajhi	8	7	6
Bank Aljazira	9	10	8
Bank Albilad	10	9	10

This tight alignment occurs because the underlying financial realities of the decision matrices create distinct, mathematically separated tiers of performance. Higher-ranked banks consistently demonstrate stronger performance across the criteria set, while lower-ranked institutions banks display shortage in performance. Because the distance between these performance tiers is substantial, shifting the weighting mechanism (CRITIC) or the ranking geometry (VIKOR) only causes minor internal reshuffling within the upper or

lower tiers, rather than large shifts across the board. This minimal variance indicates that the primary Entropy–TOPSIS framework is structurally stable and effectively measures the relative financial performance of the sector.

Table 10. Comparative ranking across distinct MCDM algorithms (2023).

Bank	Entropy–TOPSIS	Entropy–VIKOR	CRITIC–TOPSIS
SAB	1	1	1
Arab National Bank (ANB)	2	3	2
SNB	3	2	3
Alriyadh	4	4	4
The Saudi Investment Bank	5	5	5
Banque Saudi Fransi (BSF)	6	6	6
Alrajhi	7	7	9
Alinma Bank	8	8	8
Bank Aljazira	9	10	7
Bank Albilad	10	9	10

Table 11. Comparative ranking across distinct MCDM algorithms (2024).

Bank	Entropy–TOPSIS	Entropy–VIKOR	CRITIC–TOPSIS
SAB	1	1	1
SNB	2	2	3
Arab National Bank (ANB)	3	3	2
Alriyadh	4	4	4
Banque Saudi Fransi (BSF)	5	5	5
The Saudi Investment Bank	6	6	6
Alinma Bank	7	7	7
Alrajhi	8	8	10
Bank Aljazira	9	10	8
Bank Albilad	10	9	9

Table 12. Comparative ranking across distinct MCDM algorithms (2025).

Bank	Entropy–TOPSIS	Entropy–VIKOR	CRITIC–TOPSIS
Arab National Bank (ANB)	1	2	2
Banque Saudi Fransi (BSF)	2	3	4
SNB	3	1	1
Alriyadh	4	4	3
Bank Aljazira	5	5	5
Bank Albilad	6	6	6
Alrajhi	7	7	9
SAB	8	8	7
The Saudi Investment Bank	9	9	8
Alinma Bank	10	10	10

5.4.1. The 2025 Ranking Variance Between SNB and ANB

While the models are broadly consistent, the slight rank variations provide valuable insights into how different algorithms penalize or reward specific financial behaviors. These mechanical differences are illustrated in the 2025 evaluations of the Arab National Bank (ANB) and the Saudi National Bank (SNB). Under the baseline Entropy–TOPSIS model, ANB secured the number one rank, while SNB ranked third. However, when processed through Entropy–VIKOR and CRITIC–TOPSIS, SNB overtook the lead, pushing ANB to second place.

A direct examination of the 2025 raw decision matrix (Table 6) explains exactly why this occurred. ANB achieved the top TOPSIS rank because it excelled in minimizing cost criteria while maximizing shareholder payouts. ANB boasted a favorable Price-to-Book ratio of 0.87 (compared to SNB’s 1.10) and a lower Price-to-Earnings multiple of 8.77 (versus SNB’s 9.38). Furthermore, ANB delivered a superior Dividend Yield of 6.19%, slightly edging out SNB’s 5.83%. Because TOPSIS rewards the optimal geometric balance of all criteria, ANB’s favorable valuation metrics pushed it closest to the ideal solution.

Conversely, VIKOR focuses heavily on penalizing individual regret, meaning a bank will lose its top rank if it shows weakness in critical operational areas. When looking at core profitability, SNB vastly outperformed ANB. SNB delivered a higher Return on Equity (12.59% vs. ANB's 11.59%), a higher Net Profit Margin (59.44% vs. 55.67%), and a substantially larger Earnings Per Share (4.04 vs. 2.47). VIKOR recognized ANB's lower EPS and operational margins as points of regret, penalizing it just enough to allow SNB's highly balanced, profit-heavy portfolio to take the top position.

5.4.2. The Case of SAB

Tracking rank mobility across the five years demonstrates how sensitive the models are to shifting corporate strategies. Examining the movement of extreme outliers highlights the real-world impact of changing financial ratios.

The most notable trajectory is that of Saudi Awwal Bank (SAB). In 2021, SAB remained in the lower quartile of the sector (ranking seventh or eighth). The raw data (Table 2) reveals why: the bank recorded a lower Return on Equity of 6.23% and a highly inflated Price-to-Earnings ratio of 21.16. However, by significantly improving its core operations, SAB demonstrated significant operational improvement, achieving the highest rank in 2023 and 2024. By 2024 (Table 5), SAB had nearly doubled its ROE to 12.29%, reduced its P/E ratio to 8.90, and increased its Dividend Yield to a strong 6.49%.

Yet, this leading position was not maintained in 2025, where SAB experienced a notable decline back to eighth place. The 2025 data (Table 6) identifies the primary driver of this rank reduction: while SAB maintained an excellent EPS of 3.81 and a strong Net Profit Margin of 60.28%, its recorded Dividend Yield dropped entirely to zero (0.00%). As established in the criteria weighting analysis, the 2025 market heavily prioritized dividend distributions, assigning it the highest entropy weight of the year. SAB's complete lack of Dividend Yield acted as a significant penalty, mathematically reducing its score across all three methodologies. This demonstrates that historical high rankings do not guarantee future positioning in an MCDM framework if a bank entirely neglects the current year's most highly weighted financial indicator.

5.5. Four-Dimensional Sensitivity Analysis

Across all five reporting periods, Dividend Yield (C5) absorbed a disproportionate share of the objective Entropy weight, which meant that the entire ranking architecture rested, to a non-trivial extent, on the informational variance of a single indicator. This concentration is not in itself a defect of the framework—it is a direct reflection of how unevenly the eight criteria are distributed across the ten banks—but it does raise a legitimate question of inferential durability. A dynamic sensitivity analysis was therefore essential to verify that the Entropy-TOPSIS rankings were not an artifact of this concentration. Following the protocol established in comparable MCDM validation studies (Yang et al., 2019), four complementary robustness tests were conducted: (i) a Weight Perturbation Analysis (WPA), in which the weight of Dividend Yield (W_5) was attenuated by successive penalties of 30%, with the resulting deficit redistributed uniformly across the remaining seven criteria so that the unit-sum constraint $\sum W_j = 1$ was preserved at every step; (ii) a Leave-One-Criterion-Out (LOO) test, in which the Dividend Yield criterion was removed entirely and the retained weights were renormalized, representing a stringent stress test given C5's dominance; (iii) an Alternative Normalization comparison, in which the baseline Vector normalization was replaced with Max–Min scaling to verify that ranking outcomes are not artifacts of the specific normalization technique; and (iv) an Equal-Weight scenario, in which a uniform weighting of $W_j = 1/8 = 12.5\%$ was applied to all eight criteria, testing whether the Entropy-derived weights contribute analytically meaningful differentiation

beyond naive equal weighting. Figures 1–5 present the year-by-year ranking stability across all five scenarios—Baseline (Entropy-TOPSIS), WPA (−30% DY), LOO (excluding DY), Alt Normalization (Max-Min), and Equal-Weight—for the same period.

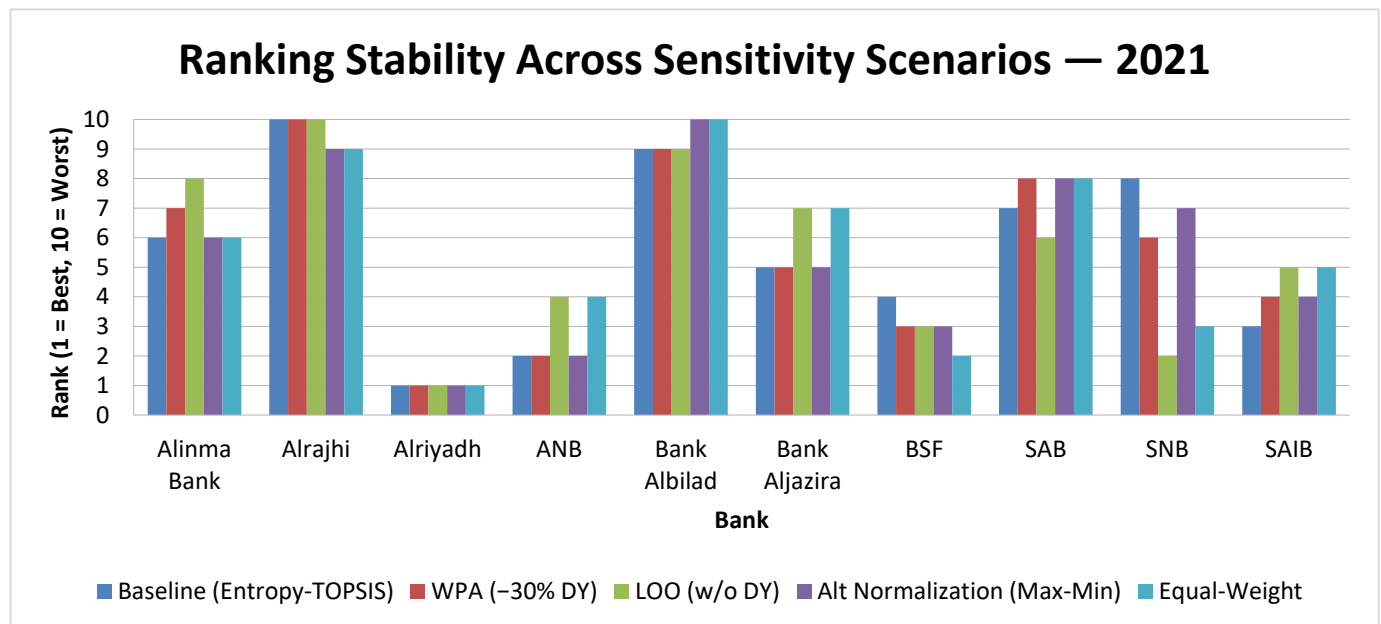


Figure 1. Rank stability across sensitivity scenarios (2021).

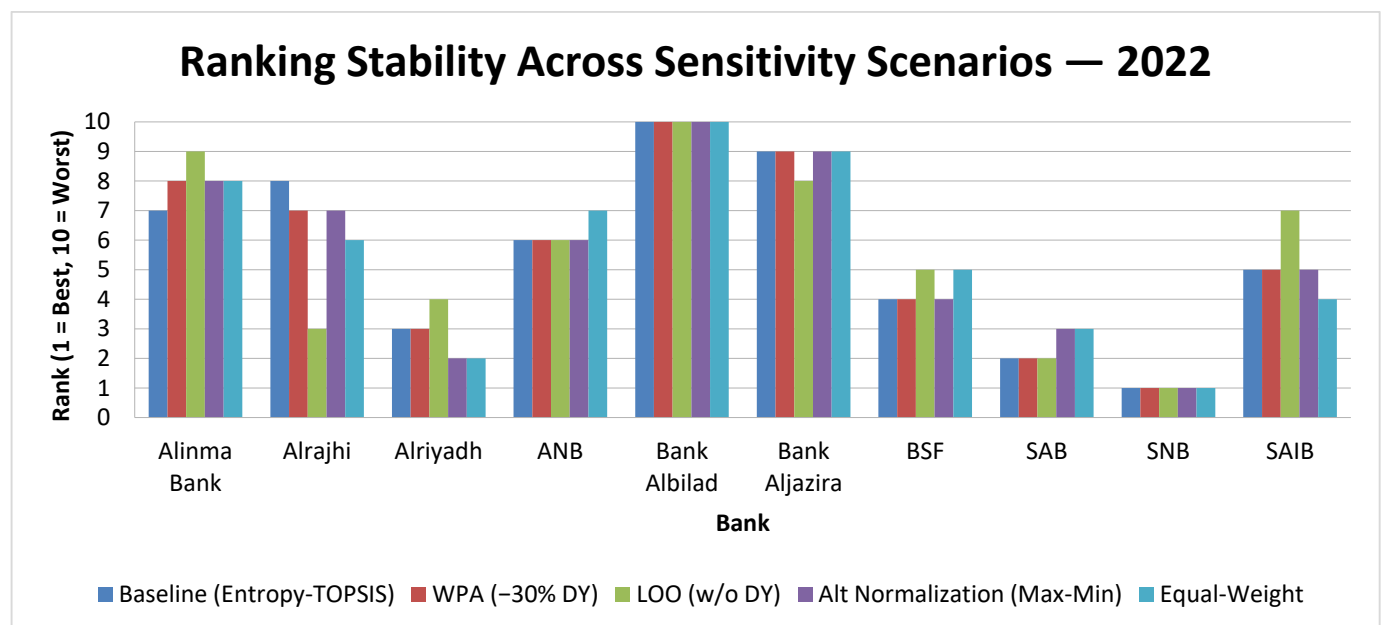


Figure 2. Rank stability across sensitivity scenarios (2022).

5.5.1. Weight Perturbation Analysis (WPA)

The Weight Perturbation Analysis examines the ranking response to a 30% attenuation of the Dividend Yield weight (W_5), with the freed weight redistributed uniformly across the remaining seven criteria. This choice represents a substantial perturbation of the most influential criterion, providing a stringent test of ranking stability. Across the five reporting years, the impact of the perturbation is remarkably contained: the majority of banks retain their baseline positions, and rank movements—where they occur—are confined to single-position shifts among institutions whose closeness coefficients are already separated by

narrow margins. In 2021, the most notable movements involved Saudi National Bank (SNB) rising from position 8 to 6 and BSF improving from 4 to 3, while SAIB and Alinma each slipped by one rank. The pattern in 2023 is similar: SNB improved from 3 to 2 and BSF from 6 to 5, offset by minor drops for ANB from 2 to 3 and Alinma from 8 to 9. Notably, no top-three position is surrendered across any year under WPA, no bottom-quartile bank breaks into the upper half, and the leading positions in each year—Alriyadh in 2021, SNB in 2022, SAB in 2023 and 2024, and ANB in 2025—remain fully intact. Figures 1–5 graphically confirm these localized adjustments, and the Spearman rank correlation between the baseline and perturbed orderings remains close to unity throughout, confirming that the ranking architecture is not artificially propped up by the elevated Dividend Yield weight. And the Spearman rank correlation between the baseline and perturbed orderings remains close to unity throughout as presented in Figure 6, confirming that the ranking architecture is not artificially propped up by the elevated Dividend Yield weight.

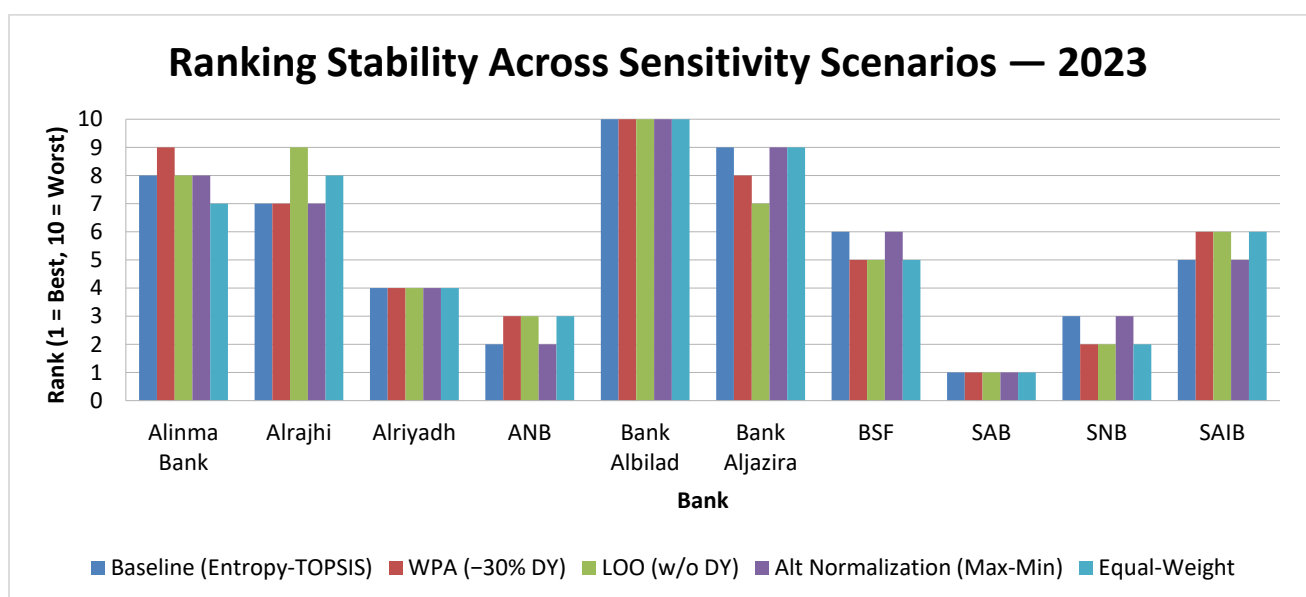


Figure 3. Rank stability across sensitivity scenarios (2023).

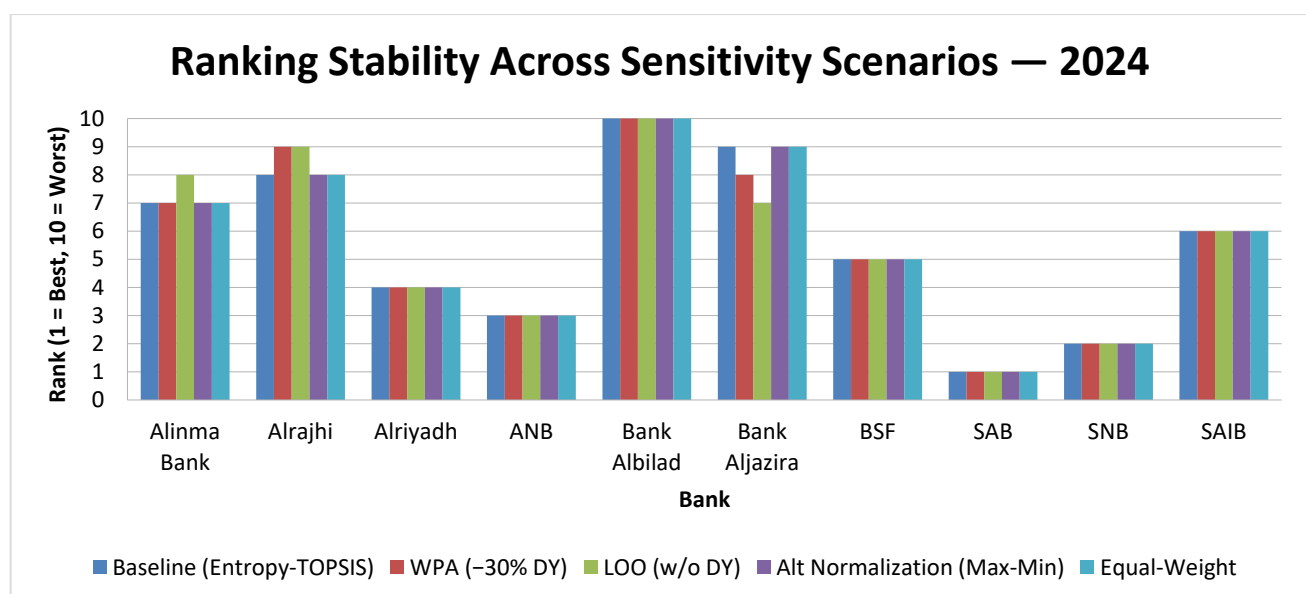


Figure 4. Rank stability across sensitivity scenarios (2024).

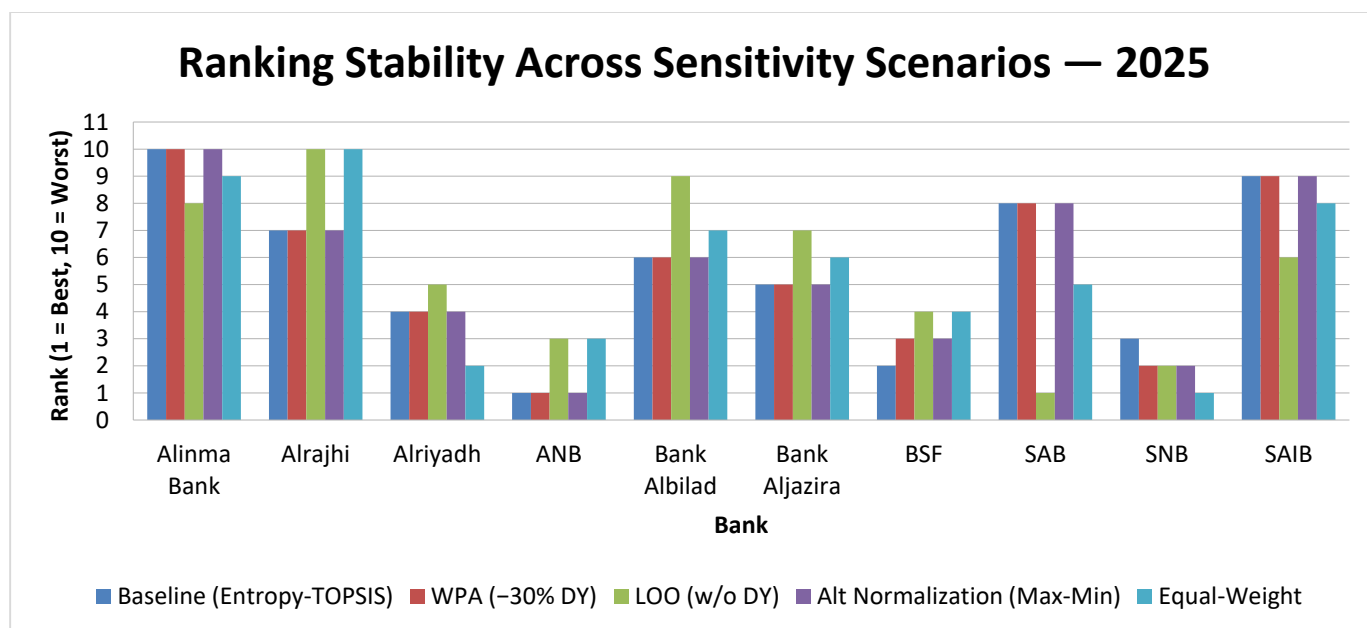


Figure 5. Rank stability across sensitivity scenarios (2025).

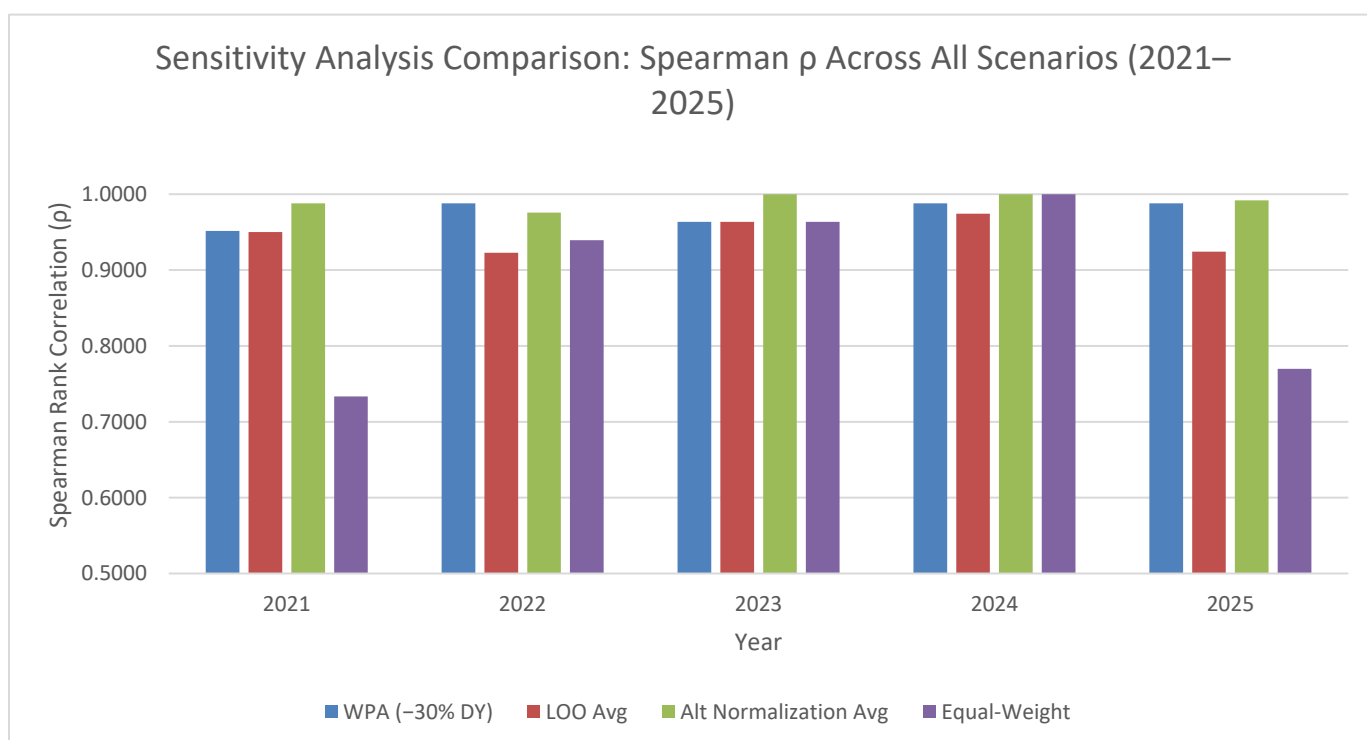


Figure 6. Sensitivity analysis comparison: Spearman ρ across all scenarios (2021–2025).

5.5.2. Leave-One-Criterion-Out (LOO) Test

The Leave-One-Criterion-Out test represents the most stringent stress applied to the Entropy-TOPSIS framework: the Dividend Yield criterion—which consistently carries the highest Entropy weight across the observation window (peaking at 53.23% in 2025)—was removed entirely, and the retained seven weights were renormalized to preserve the unit-sum constraint. The rationale for targeting Dividend Yield is that if the ranking structure remains stable under the removal of the most influential criterion, it will remain stable under the removal of any lower-weighted criterion. As shown in Figures 1–5, the LOO scenario produces the largest rank movements across all four sensitivity tests, particularly

in 2025 where SAB shifts dramatically from position 8 to 1, reflecting the removal of the substantial penalty it incurred from its zero recorded Dividend Yield. Similarly, in 2021, SNB rises from 8 to 2, and in 2022, Al Rajhi advances from 8 to 3—both consistent with these banks' underperformance on Dividend Yield relative to their operational and valuation profiles. Conversely, banks whose baseline strength derives partly from strong dividend payouts such as ANB in 2025 dropped from 1 to 3, BSF in 2025 dropped from 2 to 4, and Alrajhi in 2025 dropped 7 to 10; note the moderate ranking softening. Despite these displacements, the top-ranked bank changes only in 2025 (from ANB to SAB), and the overall Spearman correlation with the baseline remains sufficiently high to confirm that the ranking hierarchy is not artificially propped up by C5's elevated weight as presented in Figure 6—the observed shifts reflect genuine informational content of the removed criterion rather than instability in the framework.

5.5.3. Alternative Normalization Comparison

The Alternative Normalization test replaces the baseline Vector normalization with Max–Min scaling while retaining the Entropy-derived weights, isolating the effect of the normalization technique itself. Vector normalization preserves cross-criterion proportionality by dividing each raw value by the Euclidean norm of its column, whereas Max–Min scaling linearly rescales each criterion to the $[0, 1]$ interval bounded by the observed minimum and maximum. As shown in Figures 1–5, the ranking outcomes under Max–Min normalization closely mirror the baseline Vector rankings across all five reporting years, with the smallest overall divergence among the four sensitivity tests. In 2023 and 2024, the two rankings are identical for all ten banks—no rank displacement whatsoever. In 2021, minor adjustments include BSF improving from 4 to 3 and SNB rising from 8 to 7, while in 2022, Alriyadh advances from 3 to 2 and Al Rajhi improves from 8 to 7. In 2025, only two positions shift: SNB from 3 to 2 and BSF from 2 to 3. These near-identical results confirm that the ranking outcomes are not artifacts of the specific normalization technique employed but reflect genuine cross-sectional differentiation in the underlying financial performance of the ten Saudi banks. The choice of normalization method therefore does not fundamentally alter the ranking structure.

5.5.4. Equal-Weight Scenario

The Equal-Weight scenario applies a uniform weighting of $W_j = 1/8 = 12.5\%$ to all eight criteria, effectively testing whether the Entropy-derived weights contribute analytically meaningful differentiation beyond naive equal weighting. This scenario produces substantial rank shifts in several years, revealing that Entropy weighting is not redundant with equal weighting. In 2025, the divergence is particularly striking: SAB rises from position 8 to 5 as the substantial dividend penalty is diluted across all criteria, while SNB advances from 3 to 1 and Al Rajhi drops from 7 to 10, reflecting the offsetting effect of equal weighting on its elevated valuation multiples (P/E , P/B) versus its stronger profitability metrics (ROE , NPM). In 2021, similarly notable shifts include SNB rising from 8 to 3, BSF improving from 4 to 2, and Aljazira dropping from 5 to 7. In 2023, Alinma and SNB each improve by one position, while ANB and SAIB soften. The 2024 rankings, however, are fully identical to the baseline, indicating that in that year the Entropy weights and equal weights converge in their ranking implications. These localized but meaningful shifts confirm that the Entropy method captures cross-sectional variance from the raw data that materially informs the ranking outcomes—variance that a naive equal-weight approach would fail to capture. The Entropy-derived weights therefore contribute distinct analytical value.

5.5.5. Synthesis of Robustness Evidence

Taken together, the four sensitivity tests provide converging evidence that the Entropy–TOPSIS ranking architecture is robust across multiple independent dimensions of methodological perturbation. The Alternative Normalization test produces the highest degree of rank preservation (identical rankings in 2023 and 2024), followed by the Weight Perturbation Analysis (only single-position adjacent shifts across all years). The Leave-One-Criterion-Out and Equal-Weight scenarios produce more substantial rank movements—as expected, given that they represent the most consequential structural changes—yet the observed shifts consistently reflect genuine informational content rather than instability in the framework itself. Banks whose baseline strength depends heavily on Dividend Yield (SAB, SNB, ANB) see their rankings adjust when C5 is neutralized or diluted, while banks whose baseline positions derive from operational efficiency (Alriyadh, BSF) remain remarkably stable across all four tests. This multidimensional robustness matters substantively as well as methodologically: it indicates that the relative performance hierarchy of the ten Saudi banks reflects genuine multi-criteria differentiation rather than an artifact of Dividend Yield’s elevated weight, of the specific normalization technique employed, or of any single methodological choice. The Entropy–TOPSIS framework, as calibrated in this study, therefore produces empirically stable rankings that support the interpretive validity of the results reported in this study.

6. Limitation and Boundaries of the Study

While the Entropy–TOPSIS framework provides a rigorous ranking of Saudi banking institutions, several boundaries warrant acknowledgment.

First, the framework adopts an investor-oriented scope by design, focusing on eight publicly disclosed indicators encompassing profitability, valuation, and shareholder returns. This scope excludes bank-specific regulatory indicators (Capital Adequacy Ratio, Non-Performing Loans, Liquidity Coverage Ratio, Cost-to-Income Ratio, Loan Growth) that serve regulatory supervision under Basel III and CAMELS frameworks. It also excludes forward-looking credit risk parameters such as Expected Credit Loss (ECL) provisions under IFRS 9. Future research could develop complementary regulatory-oriented rankings incorporating these dimensions.

Second, the analysis is bounded temporally by the 2021–2025 window. While this period captures post-pandemic recovery and Vision 2030’s initial implementation, longer horizons may reveal cyclical or structural dynamics not visible within five years.

Third, the study focuses exclusively on the ten primary commercial banks listed on TASI, excluding foreign banks operating in Saudi Arabia, specialized financing institutions, and emerging fintech providers. Future research could broaden the sample to capture the full spectrum of financial intermediaries in the Kingdom’s evolving financial ecosystem.

Fourth, the Entropy weighting method is grounded in observed variance of raw data. As disclosure comparability improves under IFRS convergence and SAMA supervision, informational variance may evolve, potentially altering the relative influence of specific criteria. Practitioners should recompute weights rather than assume stability of the 2021–2025 weight structure.

Fifth, the 2025 fiscal-year figures rely on interim trailing-twelve-months (TTM) data extracted from MarketScreener as of the 15 February 2026 collection cutoff, prior to the release of most Saudi banks’ fully audited FY2025 annual reports. Once audited FY2025 statements become uniformly available, replication with strictly audited annual data would strengthen the study’s reproducibility and could yield minor refinements in the Ci scores. This limitation is intrinsic to real-time empirical analysis conducted at the frontier of the observation window.

Finally, as a purely retrospective and quantitative framework, the analysis cannot account for forward-looking, strategic variables such as executive leadership quality, corporate governance agility, or institutional capacity to adapt to prospective SAMA regulatory shifts. These qualitative dimensions warrant complementary assessment through mixed-methods approaches in future research.

7. Conclusions and Future Directions

This research applies an established, objective MCDM framework—Entropy–TOPSIS, cross-validated with CRITIC and VIKOR—to systematically evaluate the financial vitality of the Saudi banking sector over 2021–2025, offering an investor-oriented ranking situated within the Vision 2030 economic transformation context. The inclusion of comprehensive multi-year tracking (2021–2025) demonstrates that institutions like the Arab National Bank (ANB) and Saudi National Bank (SNB) demonstrate an effective balance between maximizing profitability metrics and minimizing cost-based risk criteria.

These findings have several practical implications. The transition from subjective narrative analysis to algorithmic rigor provides foreign institutional investors, domestic retail traders, and policymakers with a transparent, data-driven baseline of relative financial performance. As the Saudi economy continues to diversify rapidly under Vision 2030, banking institutions that can successfully balance aggressive state-backed lending portfolios with disciplined, attractive equity valuations will remain the highly stable institutions support regional growth. Furthermore, the rigorous validation protocols executed in this study—combining VIKOR, CRITIC, and four-dimensional sensitivity analysis—reinforce the methodological robustness of these findings, demonstrating that the sector’s hierarchy is structurally stable and not an artifact of a single algorithm.

Furthermore, the model strictly penalizes high valuations and short-term capital expenditure. It cannot quantify a bank’s strategic willingness to endure short-term liquidity costs to fund long-term, structurally vital giga-projects (such as NEOM or the Red Sea Project), which may temporarily hurt standard metrics but ensure secure long-term resilience. Future academic research should therefore explore hybrid MCDM frameworks—such as integrating Entropy with the BWM to fuse objective data variance with strategic, subjective expert foresight, thereby capturing the complete, nuanced reality of financial evolution in transitional economies. Beyond risk-criterion refinement, the framework could be extended into a fully algorithmic asset-allocation engine, benchmarked against established portfolio-construction paradigms such as Markowitz’s Portfolio Theory (Markowitz, 1952) and the Kelly criterion (Kelly, 1956), to assess whether Entropy–TOPSIS rankings translate into superior risk-adjusted portfolio performance. A natural parallel extension lies in reformulating the problem as a multi-objective optimization—for instance, jointly maximizing Dividend Yield and earnings quality while minimizing acquisition cost (stock price) and valuation multiples—which would convert the descriptive ranking framework into a prescriptive investment-selection tool.

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Data Availability Statement: The data supporting the findings of this study are publicly available. Financial data for the 2021–2024 fiscal years were obtained from fully audited annual consolidated statements published on the Saudi Exchange (Tadawul) issuer platform, prepared in accordance with International Financial Reporting Standards (IFRS) as endorsed in the Kingdom of Saudi Arabia and standards issued by the Saudi Organization for Chartered and Professional Accountants (SOCPA). For the 2025 fiscal year, figures represent interim trailing-twelve-months (TTM) data extracted from MarketScreener (<https://www.marketscreener.com>, accessed on 15 February 2026), compiled from Q4 2025 preliminary disclosures published on Tadawul and each bank’s Investor Relations releases. The processed decision matrices supporting the reported results are provided in Appendix A.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

This appendix presents the raw decision matrices used in the Entropy–TOPSIS analysis for the ten Saudi banking institutions across the 2021–2025 observation window. Tables A1–A5 report the values of the eight financial criteria—ROE, ROA, NPM, P/S, Dividend Yield, P/E, P/B, and EPS—for each fiscal year.

Table A1. Raw decision matrix for saudi banks (2021).

Bank	C1	C2	C3	C4	C5	C6	C7	C8
Alinma Bank	0.0983	0.0164	50.17%	8.89	0.0357	18.41	1.56	0.87
Alrajhi	0.2352	0.027	63.1%	15.17	0.0000	24.04	5.27	2.46
Alriyadh	0.1315	0.019	56.23%	7.59	0.047	13.49	1.72	1.51
Arab National Bank (ANB)	0.0713	0.0117	45.94%	7.24	0.0439	15.75	1.1	1.09
Bank Albilad	0.1485	0.0163	42.01%	8.66	0.0000	20.61	2.9	1.13
Bank Aljazira	0.0797	0.0103	33.97%	5.34	0.039	16.37	1.14	0.75
Banque Saudi Fransi (BSF)	0.0881	0.0168	54.9%	9.02	0.0386	17.46	1.43	1.3
SAB	0.0623	0.0118	44.35%	9.39	0.032	21.16	1.28	1.56
Saudi Investment Bank	0.1052	0.0169	51.63%	11.77	0.0293	23.45	1.76	2.24
Saudi National Bank (SNB)	0.0671	0.0105	42.52%	5.91	0.044	15.43	0.9	0.8

Table A2. Raw decision matrix for saudi banks (2022).

Bank	C1	C2	C3	C4	C5	C6	C7	C8
Alinma Bank	0.115	0.0193	53.13%	9.61	0.0326	18.87	2.04	1.16
Alrajhi	0.2048	0.0248	64.54%	11.32	0.0271	17.74	3	2.86
Alriyadh	0.1357	0.0205	57.02%	7.74	0.0431	13.72	1.7	1.74
Arab National Bank (ANB)	0.0966	0.0151	51.02%	7.99	0.0418	15.66	1.49	1.54
Bank Albilad	0.1641	0.0173	44.86%	9.58	0.0119	21.35	3.32	1.39
Bank Aljazira	0.0806	0.0101	34.56%	4.88	0.0000	15.16	1.15	0.81
Banque Saudi Fransi (BSF)	0.0912	0.016	53.7%	7.32	0.0479	14.54	1.26	1.35
SAB	0.0906	0.0166	53.58%	8.8	0.0398	16.58	1.47	2.37
Saudi Investment Bank	0.1137	0.0201	59.33%	7.16	0.0398	12.44	1.34	3.03
Saudi National Bank (SNB)	0.0911	0.0143	49.06%	5.62	0.0508	12.7	1.03	1.09

Table A3. Raw decision matrix for saudi banks (2023).

Bank	C1	C2	C3	C4	C5	C6	C7	C8
Alinma Bank	0.1462	0.0221	57.42	9.17	0.0236	16.66	2.25	1.55
Alrajhi	0.1606	0.0212	63.86	13.29	0.042	21.9	3.24	2.63
Alriyadh	0.1382	0.0216	57.77	6.13	0.0562	11.04	1.42	1.94

Table A3. *Cont.*

Bank	C1	C2	C3	C4	C5	C6	C7	C8
Arab National Bank (ANB)	0.1196	0.0188	51.55	4.81	0.062	9.32	1.06	2.04
Bank Albilad	0.1653	0.0174	47.58	9.13	0.0115	19.19	2.98	1.59
Bank Aljazira	0.0679	0.0083	32.84	4.94	0.0000	17.38	0.93	0.69
Banque Saudi Fransi (BSF)	0.1054	0.0174	54.63	6.2	0.0548	11.99	1.16	1.61
SAB	0.1202	0.0209	57.64	6.41	0.0564	11.12	1.26	3.41
Saudi Investment Bank	0.1171	0.0203	59.44	6.82	0.0517	11.94	1.3	3.23
Saudi National Bank (SNB)	0.1036	0.0147	48.83	4.42	0.0595	10.01	0.93	1.28

Table A4. Raw decision matrix for saudi banks (2024).

Bank	C1	C2	C3	C4	C5	C6	C7	C8
Alinma Bank	0.1539	0.0227	58.96	7.32	0.0397	13.14	1.75	1.85
Alrajhi	0.1716	0.0222	65.88	12.64	0.044	20.25	3.07	3.11
Alriyadh	0.1449	0.0222	59.56	5.47	0.0643	9.51	1.25	2.25
Arab National Bank (ANB)	0.1331	0.0211	56.08	4.8	0.0675	8.49	1.09	2.48
Bank Albilad	0.1757	0.0188	50.64	8.81	0.0156	17.39	2.92	1.88
Bank Aljazira	0.0728	0.0088	35.56	5.54	0.0000	18.52	1.1	0.81
Banque Saudi Fransi (BSF)	0.1026	0.0166	53.6	4.64	0.0658	9.22	0.83	1.72
SAB	0.1229	0.0213	60	5.14	0.0649	8.9	1	3.78
Saudi Investment Bank	0.114	0.0197	60.53	5.67	0.0618	9.72	1.03	3.44
Saudi National Bank (SNB)	0.102	0.0136	50.32	4.66	0.0554	10.14	0.86	1.43

Table A5. Raw decision matrix for saudi banks (2025).

Bank	C1	C2	C3	C4	C5	C6	C7	C8
Alinma Bank	0.1427	0.0218	58.99%	5.62	0.0000	10.34	1.26	1.97
Alrajhi	0.1866	0.0246	67.42%	10.61	0.0385	16.66	2.73	3.90
Alriyadh	0.1447	0.0215	61.22%	4.77	0.0526	8.24	1.07	2.47
Arab National Bank (ANB)	0.1159	0.0193	55.67%	4.71	0.0619	8.77	0.87	2.47
Bank Albilad	0.1603	0.0186	50.73%	6.19	0.0403	12.56	1.74	1.99
Bank Aljazira	0.0768	0.0096	36.63%	3.48	0.0467	11.19	0.66	1.00
Banque Saudi Fransi (BSF)	0.1095	0.0178	56.07%	4.37	0.0636	8.53	0.82	1.97
SAB	0.1136	0.0198	60.28%	4.75	0.0000	8.50	0.84	3.81
Saudi Investment Bank	0.1116	0.0147	54.77%	3.70	0.0000	7.83	0.73	1.68
Saudi National Bank (SNB)	0.1259	0.0216	59.44%	5.89	0.0583	9.38	1.10	4.04

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