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# Evaluating Stocks with a Subjectively Rational Approach

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## Abstract

This paper proposes a structured, multi-criteria framework for stock evaluation grounded in the principles of rationally subjective decision-making. Building on rational choice theory and bounded rationality, the methodology adapts the Rational Approach to financial analysis by integrating multiple dimensions - risk, profitability, valuation, growth, dividends, and quality - into a weighted scoring system. The proposed Rational Approach serves as an explicit mathematical compromise: it limits cognitive overload (resource-rational) while allowing managers to inject institutional priorities without relying on "black-box" proprietary algorithms. For illustration, the framework is applied to the *Magnificent Seven* technology companies, with each firm graded across categories using point-in-time financial metrics sourced from publicly available data. Scores are normalized to a 0-100 scale, ensuring comparability and transparency without reliance on analyst forecasts or proprietary algorithms. The study demonstrates how rational weighting schemes can enhance investor efficiency by balancing expected returns against uncertainty while remaining accessible to both institutional and individual investors. Beyond its immediate application, the framework offers a pedagogical bridge between decision theory, behavioral finance, and empirical stock analysis. Future research directions include methodological refinements through adaptive weighting, empirical validation across sectors and geographies, benchmarking against established rating systems, and integration of qualitative dimensions such as governance, environmental, social, and corporate responsibility factors. Collectively, the findings underscore the potential of subjectively rational, multi-criteria grading methodologies to advance academic discourse and provide practical tools for transparent, reproducible, and bias-resistant investment decision-making.

Keywords: Investment Theory, Stock Rating, Finance, Portfolio Theory, Decision-making.

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## 1. Introduction

The rational decision-making model has long served as a cornerstone of organizational and financial analysis. Rooted in Simon's (1955) work, rational choice theory emphasizes the systematic evaluation of alternatives through defined objectives and quantifiable criteria. Simon's notion of bounded rationality acknowledges the limits

of human cognition and information availability, yet it still provides a framework for structured, transparent decision-making. This foundation is particularly relevant to financial markets, where investors must balance multiple, often conflicting objectives under uncertainty.

Building on these foundations, the field of multi-criteria decision analysis (MCDA) has developed methodologies for evaluating alternatives across diverse dimensions. Keeney and Raiffa (1993) formalized the weighted sum model, which remains widely applied in finance and operations research. Triantaphyllou (2000) further compared MCDA methods such as Analytic Hierarchy Process (AHP), TOPSIS, and ELECTRE, highlighting their strengths and limitations in contexts requiring trade-offs among competing objectives. These frameworks underpin stock grading systems that integrate risk, profitability, valuation, and other financial metrics into composite scores.

In practice, several proprietary rating systems have gained prominence. Zacks Investment Research (2026) emphasizes earnings estimate revisions and surprises, aligning ratings with short-term momentum. Morningstar's Stock ratings (2026) focus on intrinsic value and economic moat analysis, reflecting a long-term, fundamental orientation. Seeking Alpha's Quant Ratings (2026) employ multi-factor scoring-including valuation, growth, profitability, and momentum-offering a transparent, factor-based alternative. Comparative studies underscore the diversity of approaches, ranging from analyst-driven qualitative assessments to algorithmic, data-driven models.

Recent advances in decision science by Lieder & Griffiths (2020) have introduced the concept of resource-rationality, which frames human and algorithmic decision-making as the optimal use of limited computational resources. This perspective is particularly relevant to stock grading methodologies, which must balance complexity, transparency, and usability. By adopting a rational yet resource-conscious framework, grading systems can mitigate behavioral biases such as anchoring, recency, and herd behavior while remaining accessible to practitioners.

In addition to the decision-theoretic foundations discussed above, a substantial body of empirical finance research provides important context for stock evaluation frameworks. Modern asset-pricing studies have demonstrated that firm characteristics systematically relate to expected returns, forming the basis of factor investing. The seminal work of Fama et al. (1992, 1993) introduced size and value factors, later expanded into profitability and investment factors in their five-factor model Fama et al., (2015). Carhart (1997) added momentum as a fourth factor, while subsequent research identified additional characteristics such as operating profitability, Novy-Marx (2013)] including value-momentum-profitability-investment composites such as the Quality Minus Junk framework of Asness et al. (2013) and investment efficiency (Hou, et al. (2015). These multifactor models provide a benchmark for understanding how quantitative signals predict returns and illustrate how composite characteristics can be aggregated into systematic scoring frameworks.

Parallel to factor investing, a large literature examines stock screening and composite indicators. Classic examples include Piotroski's (2000) F-score, Altman's (1968) Z-score, and Ohlson's (1980) O-score, all of which demonstrate how fundamental variables can be combined into interpretable, rule-based metrics that classify firms by financial strength. More recent work, such as Green et al. (2017), shows that composite fundamental screens often outperform individual signals, underscoring the value of multi-criteria approaches.

Portfolio optimization research also offers relevant insights. Markowitz's (1952) mean-variance framework remains foundational, but subsequent developments-including robust optimization approaches, for example see Fabozzi et al. (2010) and multi-objective portfolio-selection models by Steuer (1986), Ehrgott et al. (2010)-demonstrate that investors frequently balance multiple, sometimes conflicting objectives under uncertainty, showing that weighted-criteria frameworks can complement or substitute for traditional optimization when investors face bounded rationality or prefer transparent, interpretable decision rules.

A further point of comparison comes from quantitative rating systems used in practice. Morningstar's star ratings, Zacks Rank, and Seeking Alpha's Quant Ratings all rely on multifactor scoring methodologies that integrate valuation, growth, profitability, and momentum signals. Academic evaluations of these systems, for example, see Barber et al. (2016), show that transparent, rules-based ratings can influence investor behavior and sometimes predict returns. However, these systems typically rely on proprietary algorithms or analyst-driven inputs, limiting reproducibility.

Collectively, the literature-including Abeler et al. (2025), Ali et al. (2024), and Kobiyh et al. (2024)-shows that rational, multicriteria frameworks provide both theoretical rigor and practical value in financial decision-making. By positioning stock grading within this tradition, the present study advances ongoing discussions about how structured, transparent, and reproducible methodologies can improve the quality of investor decisions and trust

without relying on proprietary algorithms or analyst-driven overlays.

This paper applies a stock grading procedure first introduced by Kantarelis (2017), grounded in what physical scientists call the scientific method-or, more conventionally, the Rational Approach (RA) to decision-making. I propose that this framework can be adapted as an alternative methodology for evaluating stocks. Within constraints such as risk tolerance, investment horizon, and market scope, the RA requires consideration of multiple alternatives and criteria, the assignment of relative weights, and systematic grading. Decisions produced through this process are best described as rationally subjective: their rationality depends on the decision maker's ability to legally obtain information about an asset's history, the firm's current performance, and future forecasts. The more rational the process, the more efficient the investor becomes as a speculator.

The methodology offers a systematic instrument to enhance efficiency and consistency in investment decisions. For institutional investors, it provides a rigorous analytical framework that can be integrated into existing models, enabling structured evaluation across diverse asset classes. At its core is a risk-adjusted scoring mechanism that explicitly balances expected returns against uncertainty. This feature makes the approach particularly valuable for portfolio managers, as it scales across large datasets rather than being limited to individual securities, thereby surpassing intuition-based or heuristic strategies.

The grading system also serves as a normative guide in the face of uncertainty. For individual investors, its simplicity and accessibility reduce emotional bias, fostering clearer decisions with less psychological stress. Beyond its practical utility, the methodology functions as a pedagogical framework. By linking rational choice processes to established theories - such as decision theory, expected utility, and behavioral finance - it demonstrates how abstract models can be operationalized in empirical contexts, bridging the gap between theory and applied stock analysis.

In general, taken together, the strands of research mentioned above demonstrate that multi-criteria evaluation is central to both academic finance and practitioner-oriented stock analysis. By situating the Rational Approach within this broader empirical context, the proposed framework can be understood as a flexible, transparent, and rationally subjective alternative to established multifactor models. Rather than competing with predictive asset-pricing models, our methodology complements them by providing a decision-support tool that helps investors articulate priorities, structure tradeoffs, and evaluate alternatives under bounded rationality. Thus, the present study contributes to the above literature by offering a fully transparent, user-defined, and pedagogically grounded alternative that emphasizes rational weighting and interpretability rather than predictive optimization.

While traditional Multi-Criteria Decision Analysis (MCDA) assumes agents possess unbounded cognitive capacity to calculate values perfectly, our framework serves as a deliberate, resource-conscious compromise. It provides a systematic, matrix-based architecture that limits cognitive overload (satisfying resource-rationality) while allowing institutional managers to explicitly inject subjective strategic priorities via defined weights, without relying on opaque, proprietary "black-box" algorithms. The purpose of this framework is normative and point-in-time prescriptive decision-making, rather than predictive asset pricing or alpha generation (such as empirical factor models like Fama-French).

The remainder of this paper is organized as follows: Section 2 critically examines the employed methodology; Sections 3 and 4 apply the RA framework to a portfolio comprising the Magnificent Seven stocks; Section 5 discusses the practical value of stock ratings; and Section 6 concludes by comparing the proposed system with existing grading approaches and suggesting avenues for further research, including testing rational grading against behavioral biases.

## 2. Methodology

Simon (1957, 1959) contends that the rational approach is applicable primarily in non-complex situations, or those involving a limited number of well-defined alternatives and criteria. Stocks, by their nature, are well-defined alternatives. Accordingly, portfolios containing a relatively small number of stocks (e.g., 2-300, or a representative index such as the Dow Jones Industrial Average) are suitable candidates for the proposed procedure.

From an organizational and Decision Support Systems (DSS) perspective, selecting criteria and assigning weights forces a decision-maker to confront the limits of human cognition, or bounded rationality. Rather than operating as a predictive asset-pricing model, this framework functions as a normative, multi-criteria decision analysis (MCDA) tool designed to reduce cognitive load and mitigate behavioral heuristic biases (such as anchoring and herd behavior) by enforcing an explicit, reproducible decision-making architecture.

As illustrated in Figure 1, once the need for a decision is recognized, the investor must identify constraints and establish criteria. To formalize this process and remove the illusion of qualitative arbitrariness, the Decision Support System (DSS) operationalizes a deterministic Multi-Attribute Utility Theory (MAUT) variant via a multi-criteria evaluation matrix (Figure 2).

Let  $A = \{A_1, A_2, \dots, A_k\}$  be the set of  $k$  investment alternatives (stocks), and let  $C = \{C_1, C_2, \dots, C_j\}$  be the set of  $j$  evaluation criteria. The importance of each criterion is governed by a subjective weight vector  $W = \{W_1, W_2, \dots, W_j\}$  where each weight  $w_j \in [1, 100]$  reflects the institutional or individual manager's strategic priority.

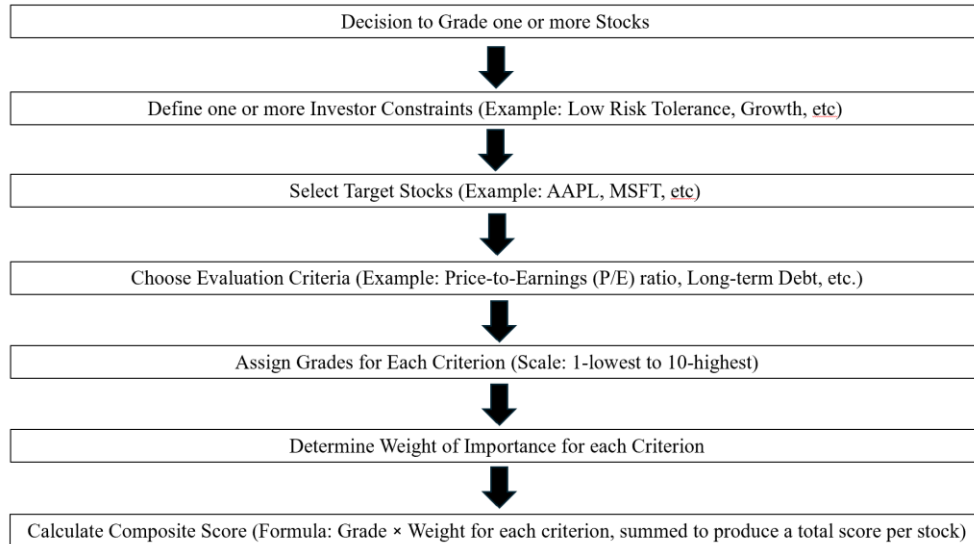


Figure 1: Rational Decision-Making Flow Chart

| Weights      | $w_1$        | $\dots$ | $w_j$        | TS                                       |
|--------------|--------------|---------|--------------|------------------------------------------|
| Criteria     | $C_1$        | $\dots$ | $C_j$        |                                          |
| Alternatives | $A_1$        | $\dots$ | $A_k$        |                                          |
|              | $w_1 G_{11}$ | $\dots$ | $w_j G_{1j}$ | $TA_1 = w_1 G_{11} + \dots + w_j G_{1j}$ |
|              | $\vdots$     | $\dots$ | $\vdots$     | $\vdots$                                 |
|              | $w_1 G_{k1}$ | $\dots$ | $w_j G_{kj}$ | $TA_k = w_1 G_{k1} + \dots + w_j G_{kj}$ |

A=Alternative, w=Weight of importance (1=lowest to 100=highest) or other,  
C=Criterion, G=Grade (1=lowest, 10=highest), TS=Total Score.

Figure 2: Rational Decision-Making Matrix

## 2.1 Grade Normalization Functions

To ensure comparability across disparate financial dimensions (e.g., comparing a ratio like P/E to a percentage like Profit Margin), raw metrics must be mapped onto a standardized grading scale  $G_{ij} \in [1, 10]$ . DSS utilizes linear data-transformation functions based on the performance bounds of the selected peer asset universe.

For **benefit criteria** (where higher values are preferable, such as Profitability or Growth), the normalized grade  $G_{ij}$  for alternative  $i$  under criterion  $j$  is calculated as:

$$G_{ij} = 1 + 9 \left( \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})} \right)$$

For **cost criteria** (where lower values are preferable, such as P/E Ratio or Debt-to-Equity), the normalized grade  $G_{ij}$  is calculated as:

$$G_{ij} = 1 + 9 \left( \frac{\max_i(x_{ij}) - x_{ij}}{\max_i(x_{ij}) - \min_i(x_{ij})} \right)$$

Where  $x_{ij}$  represents the raw point-in-time performance metric of alternative  $A_i$  under criterion  $C_j$ .

## 2.2 Mathematical Formulation of the Total Score

Once the performance metrics are normalized into dimensionless utility grades, the framework executes a Weighted Sum Model (WSM). The Total Score  $TS_i$  for each alternative  $A_i$  is the mathematically weighted aggregate of its performance across all criteria:

$$TS_i = \sum_{j=1}^n w_j G_{ij}$$

To achieve uniform interpretability across highly varied idiosyncratic weighting schemes, the final output is transformed into a Normalized Total Score  $NTS_i$  scaled from 0 to 100:

$$NTS_i = \left( \frac{TS_i}{\sum_{j=1}^n w_j 10} \right) 100$$

This explicit mathematical scaling ensures that the final output serves solely as an analytical indicator of strategic alignment, enabling managers to rank assets strictly by their adherence to defined organizational constraints. Grading and ranking portfolio stocks based on weighted criteria can be a highly valuable exercise for investors, offering several key benefits:

- **Structured Decision-Making.** Rather than relying on intuition, the investor applies a systematic framework that reduces emotional bias and promotes consistency.
- **Clarity of Priorities.** Assigning weights makes explicit what matters most (e.g., growth, dividends, or risk), ensuring that the portfolio reflects the investor's philosophy.
- **Cross-Stock Comparisons.** A grading system enables evaluation of diverse companies on a common scale - for instance, comparing a technology growth stock with a utility dividend stock more objectively.
- **Portfolio Optimization.** Rankings highlight which stocks merit greater capital allocation and which may require trimming, thereby guiding rebalancing decisions.
- **Risk Management.** Criteria such as volatility, debt levels, or sector exposure can be weighted to prevent over-concentration in high-risk areas.

However, this exercise also carries limitations and caveats:

- **Subjectivity of Criteria.** Metrics and weights reflect the investor's perspective; another investor may rank the same stocks differently. The system's value depends on the rigor of its design.

- **Dynamic Markets.** A stock's grade today may not hold tomorrow. Earnings reports, macroeconomic shifts, or industry changes can quickly alter fundamentals, necessitating regular updates.
- **Risk of Over-Simplification.** Reducing complex businesses to a single grade may obscure important nuances. For example, a firm might score poorly on short-term profitability yet excel in long-term innovation potential.
- **False Precision.** Exact weights and scores can create an illusion of mathematical certainty that markets do not provide. The framework should be viewed as guidance, not prediction.

The most effective use of this methodology is to treat it as a decision-support tool rather than a definitive verdict. It should be combined with qualitative insights, such as management quality, industry trends, and competitive positioning, and used to identify mismatches (e.g., a stock favored emotionally but ranked poorly on objective criteria). Finally, criteria should be revisited and refined over time as investment goals evolve. In short, grading and ranking is a valuable framework for discipline and clarity, but it must complement, not replace, ongoing analysis.

In the following sections (3 and 4), we explicitly frame a **corporate/institutional simulation** that demonstrates how a DSS scales and reorders assets dynamically under varying strategic organizational mandates (e.g., Growth-Focused vs. Risk-Averse vs. Income-Seeking).

### 3. Magnificent Seven Portfolio (Conventional Criteria and Weights)

Consider a portfolio that consists of the so-called Magnificent Seven stocks - Microsoft (MSFT), Apple (AAPL), Tesla (TSLA), Amazon (AMZN), Meta (META), Alphabet (GOOGL), and Nvidia (NVDA). Undoubtedly, the proposed grading system can be applied dynamically; for example, how the rankings shift when the investor changes the weights of importance. This shows how different investor profiles (growth-focused vs. risk-averse vs. dividend-seeking) reorder the Magnificent Seven. Consider the following three scenarios based on historical data up to November 25, 2025:

Table 1. Scenario 1 - Growth-Focused Investor <sup>1</sup>

| Stock               | Growth<br>(40%) | Valuation<br>(15%) | Profitability<br>(15%) | Risk<br>(10%) | Dividends<br>(5%) | Quality<br>(15%) | Total<br>Score | Normalized<br>(0-100) |
|---------------------|-----------------|--------------------|------------------------|---------------|-------------------|------------------|----------------|-----------------------|
| Apple<br>(AAPL)     | 7 → 280         | 6 → 90             | 9 → 135                | 8 → 80        | 7 → 35            | 9 → 135          | 700            | 70                    |
| Microsoft<br>(MSFT) | 8 → 320         | 7 → 105            | 9 → 135                | 8 → 80        | 6 → 30            | 9 → 135          | 740            | 74                    |
| Alphabet<br>(GOOGL) | 8 → 320         | 7 → 105            | 8 → 120                | 7 → 70        | 1 → 5             | 8 → 120          | 720            | 72                    |
| Amazon<br>(AMZN)    | 9 → 360         | 6 → 90             | 7 → 105                | 6 → 60        | 1 → 5             | 9 → 135          | 710            | 71                    |
| Meta<br>(META)      | 8 → 320         | 7 → 105            | 8 → 120                | 6 → 60        | 1 → 5             | 8 → 120          | 690            | 69                    |
| Nvidia<br>(NVDA)    | 10 → 400        | 4 → 60             | 9 → 135                | 5 → 50        | 1 → 5             | 10 → 150         | 750            | 75                    |
| Tesla<br>(TSLA)     | 9 → 360         | 4 → 60             | 6 → 90                 | 4 → 40        | 1 → 5             | 8 → 120          | 640            | 64                    |

Top scorers: Nvidia (75), Microsoft (74), Alphabet (72)

Mid-range: Amazon (71), Apple (70), Meta (69)

Lowest: Tesla (64), due to valuation and risk concerns

<sup>1</sup> Each Total Score is normalized as follows: Consider AAPL.

Total Score for AAPL when all grades are 10 =  $10(40+15+15+10+5+15) = 1000$ .

Total Score based on the earned grades = 700.

Normalized Total Score =  $(700/1000) \times 100 = 70$ .

## Justifications for Scenario 1 Grades:

- **Growth:** Nvidia and Tesla score highest due to explosive revenue growth in AI and EV sectors. Amazon also remains strong with cloud and retail expansion. Apple and Microsoft show steady but mature growth.
- **Valuation:** Nvidia and Tesla are penalized for stretched valuations relative to earnings. Microsoft and Alphabet are moderately valued, while Apple trades at a premium but justified by stability.
- **Profitability:** Apple, Microsoft, and Nvidia excel with strong margins. Amazon lags due to retail's thin margins.
- **Risk:** Tesla and Nvidia face higher volatility and sector-specific risks. Apple and Microsoft are safer due to diversified revenue streams.
- **Dividends:** Apple and Microsoft provide modest dividends; others (Amazon, Alphabet, Meta, Tesla, Nvidia) offer little to none.
- **Quality:** Microsoft, Apple, and Nvidia score highest for innovation, balance sheets, and competitive moats.

Table 2: Scenario 2 - Risk-Averse Investor

| Stock               | Risk<br>(30%) | Profitability<br>(25%) | Valuation<br>(20%) | Growth<br>(10%) | Dividends<br>(10%) | Quality<br>(5%) | Total<br>Score | Normalized<br>(0-100) |
|---------------------|---------------|------------------------|--------------------|-----------------|--------------------|-----------------|----------------|-----------------------|
| Apple<br>(AAPL)     | 8 → 240       | 9 → 225                | 6 → 120            | 7 → 70          | 7 → 70             | 9 → 45          | 770            | 77                    |
| Microsoft<br>(MSFT) | 8 → 240       | 9 → 225                | 7 → 140            | 8 → 80          | 6 → 60             | 9 → 45          | 790            | 79                    |
| Alphabet<br>(GOOGL) | 7 → 210       | 8 → 200                | 7 → 140            | 8 → 80          | 1 → 10             | 8 → 40          | 680            | 68                    |
| Amazon<br>(AMZN)    | 6 → 180       | 7 → 175                | 6 → 120            | 9 → 90          | 1 → 10             | 9 → 45          | 620            | 62                    |
| Meta<br>(META)      | 6 → 180       | 8 → 200                | 7 → 140            | 8 → 80          | 1 → 10             | 8 → 40          | 650            | 65                    |
| Nvidia<br>(NVDA)    | 5 → 150       | 9 → 225                | 4 → 80             | 10 → 100        | 1 → 10             | 10 → 50         | 615            | 62                    |
| Tesla<br>(TSLA)     | 4 → 120       | 6 → 150                | 4 → 80             | 9 → 90          | 1 → 10             | 8 → 40          | 490            | 49                    |

Top scorers: Microsoft (79), Apple (77) - balanced, profitable, lower risk.

Mid-range: Alphabet (68), Meta (65), Amazon (62), Nvidia (62).

Lowest: Tesla (49) - high growth but penalized by risk, valuation, and profitability.

## Justifications for Scenario 2 Grades:

- **Risk (30%):** Apple and Microsoft score highest (8) due to diversified revenue and stability. Tesla (4) and Nvidia (5) are riskier due to volatility and sector concentration.
- **Profitability (25%):** Apple, Microsoft, and Nvidia excel with strong margins. Amazon lags (7) due to retail's thin margins. Tesla (6) is weaker given cyclical profitability.
- **Valuation (20%):** Microsoft and Alphabet (7) are fairly valued relative to growth. Nvidia (4) and Tesla (4) are penalized for stretched multiples.
- **Growth (10%):** Nvidia (10) and Tesla (9) lead in growth potential. Amazon (9) also strong. Apple (7) and Microsoft (8) show mature but steady growth.
- **Dividends (10%):** Apple (7) and Microsoft (6) provide modest dividends. Others (Amazon, Alphabet, Meta, Nvidia, Tesla) score low (1).
- **Quality (5%):** Microsoft, Apple, and Nvidia score highest for innovation, balance sheets, and competitive moats.

Table 3: Scenario 3 - Dividend/Income Investor

| Stock               | Dividends<br>(40%) | Profitability<br>(25%) | Risk<br>(15%) | Valuation<br>(10%) | Growth<br>(5%) | Quality<br>(5%) | Total<br>Score | Normalized<br>(0-100) |
|---------------------|--------------------|------------------------|---------------|--------------------|----------------|-----------------|----------------|-----------------------|
| Apple<br>(AAPL)     | 7 → 280            | 9 → 225                | 8 → 120       | 6 → 60             | 7 → 35         | 9 → 45          | 765            | 76.5                  |
| Microsoft<br>(MSFT) | 6 → 240            | 9 → 225                | 8 → 120       | 7 → 70             | 8 → 40         | 9 → 45          | 740            | 74                    |
| Alphabet<br>(GOOGL) | 1 → 40             | 8 → 200                | 7 → 105       | 7 → 70             | 8 → 40         | 8 → 40          | 495            | 49.5                  |
| Amazon<br>(AMZN)    | 1 → 40             | 7 → 175                | 6 → 90        | 6 → 60             | 9 → 45         | 9 → 45          | 455            | 45.5                  |
| Meta<br>(META)      | 1 → 40             | 8 → 200                | 6 → 90        | 7 → 70             | 8 → 40         | 8 → 40          | 480            | 48                    |
| Nvidia<br>(NVDA)    | 1 → 40             | 9 → 225                | 5 → 75        | 4 → 40             | 10 → 50        | 10 → 50         | 480            | 48                    |
| Tesla<br>(TSLA)     | 1 → 40             | 6 → 150                | 4 → 60        | 4 → 40             | 9 → 45         | 8 → 40          | 375            | 37.5                  |

**Top scorers:** Apple (76.5), Microsoft (74.0) - strong dividends and profitability

**Mid-range:** Alphabet (49.5), Meta (48.0), Nvidia (48.0), Amazon (45.5)

**Lowest:** Tesla (37.5) - high growth, penalized heavily by lack of dividends, valuation, and risk

Justifications for Scenario 3 Grades:

- **Dividends (40%):** Apple (7) and Microsoft (6) stand out with consistent payouts. The rest (Alphabet, Amazon, Meta, Nvidia, Tesla) offer little to none, hence low scores.
- **Profitability (25%):** Apple, Microsoft, and Nvidia excel with strong margins. Tesla (6) and Amazon (7) lag due to cyclical or thin-margin businesses.
- **Risk (15%):** Apple and Microsoft (8) are safer due to diversified revenue streams. Tesla (4) and Nvidia (5) are riskier given volatility and sector concentration.
- **Valuation (10%):** Microsoft and Alphabet (7) are reasonably valued relative to growth. Nvidia (4) and Tesla (4) are penalized for stretched multiples.
- **Growth (5%):** Nvidia (10) and Tesla (9) lead in growth potential. Amazon (9) also strong. Apple (7) and Microsoft (8) show mature but steady growth.
- **Quality (5%):** Microsoft, Apple, and Nvidia score highest for innovation, balance sheets, and competitive moats.

#### 4. Magnificent Seven Portfolio (Idiosyncratic Criteria and Weights)

Criteria and their associated weights need not always follow conventional frameworks. In practice, an idiosyncratic investor may rationally select and justify a unique set of criteria that reflect personal priorities or philosophies. Table 4 illustrates this flexibility by presenting twelve criteria tailored to both high risk - tolerant and low risk - tolerant investors, together with their respective weights of importance and possible justifications. The table below offers an example of how the Magnificent Seven may be rated by such investors.

Table 4: High and Low Risk Tolerance Idiosyncratic Investors

|    | Criteria                           | Investor Tolerance & Weights |          | Justification                                                                                                                                                    |
|----|------------------------------------|------------------------------|----------|------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|    |                                    | High Risk                    | Low Risk |                                                                                                                                                                  |
| 1  | Short-term History (STH)           | 2                            | 4        | Low-risk investors care more about recent performance to avoid surprises; high-risk investors focus less on short-term noise.                                    |
| 2  | Long-term History (LTH)            | 11                           | 12       | Both profiles value long-term consistency, but low-risk investors rely on it even more for stability.                                                            |
| 3  | Current News (News)                | 1                            | 4        | Low-risk investors react more to news that could signal risk; high-risk investors often ignore short-term headlines.                                             |
| 4  | Management (MGMT)                  | 12                           | 7        | High-risk investors emphasize visionary leadership and bold strategies; low-risk investors care but prioritize financial fundamentals.                           |
| 5  | Employment (EMP)                   | 3                            | 11       | Employment stability signals financial health — crucial for low-risk investors; high-risk investors tolerate volatility.                                         |
| 6  | Short-term Debt (ST Debt)          | 6                            | 8        | Debt risk is more concerning for low-risk investors who want financial stability.                                                                                |
| 7  | Long-term Debt (LT Debt)           | 5                            | 10       | Long-term obligations weigh heavier for low-risk investors who avoid financial fragility.                                                                        |
| 8  | Forecast (Forecast)                | 7                            | 6        | High-risk investors lean more on future potential; low-risk investors are cautious but still consider forecasts.                                                 |
| 9  | Competition (Comp)                 | 8                            | 5        | High-risk investors chase disruptors and competitive edge; low-risk investors prefer stable market positions.                                                    |
| 10 | P/E Ratio (P/E)                    | 9                            | 3        | High-risk investors tolerate high P/E for growth potential; low-risk investors prefer value stocks with lower P/E.                                               |
| 11 | Growth past year (Growth 1y)       | 10                           | 2        | High-risk investors chase recent momentum; low-risk investors distrust short-term spikes.                                                                        |
| 12 | Growth past five years (Growth 5y) | 7                            | 9        | Long-term growth is moderately important for high-risk investors to validate momentum, but it is critical for low-risk investors who rely on proven consistency. |

Using these 12 criteria and weights, possible results of how an idiosyncratic investor grades and justifies the assigned grades are displayed in Table 5 (high-risk tolerance investor) and Table 6 (low-risk tolerance Investor)<sup>2</sup> based on historical data up to November 26, 2025.

Table 5: High-risk tolerance Idiosyncratic Investor

| Company          | STH (2) | LTH (11) | News (1) | MGMT (12) | EMP (3) | ST Debt (6) | LT Debt (5) | Forecast (7) | Comp (8) | P/E (9) | Growth 1y (10) | Growth 5y (7) | Total Score (TS) | Normalized TS (0–100) |
|------------------|---------|----------|----------|-----------|---------|-------------|-------------|--------------|----------|---------|----------------|---------------|------------------|-----------------------|
| Apple (AAPL)     | 9→18    | 10→110   | 8→8      | 9→108     | 8→24    | 9→54        | 8→40        | 9→63         | 7→56     | 6→54    | 8→80           | 9→63          | 678              | 89                    |
| Microsoft (MSFT) | 9→18    | 10→110   | 9→9      | 10→120    | 9→27    | 9→54        | 9→45        | 9→63         | 8→64     | 7→63    | 9→90           | 9→63          | 690              | 91                    |
| Alphabet (GOOGL) | 10→20   | 10→110   | 9→9      | 9→108     | 9→27    | 8→48        | 8→40        | 10→70        | 8→64     | 7→63    | 10→100         | 10→70         | 700              | 92                    |
| Amazon (AMZN)    | 8→16    | 9→99     | 7→7      | 8→96      | 8→24    | 7→42        | 7→35        | 8→56         | 7→56     | 6→54    | 8→80           | 8→56          | 640              | 85                    |
| Meta (META)      | 7→14    | 8→88     | 7→7      | 8→96      | 7→21    | 7→42        | 7→35        | 8→56         | 7→56     | 6→54    | 8→80           | 7→49          | 610              | 81                    |
| Tesla (TSLA)     | 6→12    | 7→77     | 6→6      | 7→84      | 6→18    | 6→36        | 5→25        | 7→49         | 8→64     | 5→45    | 7→70           | 6→42          | 560              | 74                    |
| Nvidia (NVDA)    | 10→20   | 9→99     | 9→9      | 9→108     | 8→24    | 8→48        | 8→40        | 10→70        | 9→72     | 6→54    | 10→100         | 10→70         | 720              | 95                    |

Hence, this high-risk tolerant investor, in the top-tier ranks Nvidia, Alphabet, and Microsoft - clear leaders driven by AI and cloud dominance. In the mid-tier she ranks Apple, Amazon, and Meta - strong fundamentals but

<sup>2</sup> In this case, weights have been assigned as follows: w=Weight of importance ( $1 \leq w \leq j$ ,  $j$ =number of criteria or  $1 \leq w \leq 12$ , 1=lowest, 12=highest).

facing valuation or competitive pressures. In the lower-tier she ranks Tesla - innovative but riskier, with weaker fundamentals compared to peers.

A high-risk tolerance Idiosyncratic Investor may justify the assignments for the weights of importance as follows:

- Apple: Strong long-term history, services growth, premium valuation drags P/E.
- Microsoft: AI/cloud leadership, Nadella highly rated, balanced debt and growth.
- Alphabet (Google): Gemini AI success, strongest 2025 rally, diversified revenue streams.
- Amazon: AWS growth strong, retail margins pressured, debt manageable.
- Meta: AI diversification promising, FTC victory, but regulatory risks and volatility.
- Tesla: Innovation-heavy, but volatile, debt-sensitive, valuation stretched.
- Nvidia: AI chip dominance, record revenues, highest score overall despite valuation risk.

Table 6: Low-risk tolerance Idiosyncratic Investor

| Company             | STH<br>(4) | LTH<br>(12) | News<br>(4) | MGMT<br>(7) | EMP<br>(11) | ST Debt<br>(8) | LT Debt<br>(10) | Forecast<br>(6) | Comp<br>(5) | P/E<br>(3) | Growth 1y<br>(2) | Growth 5y<br>(9) | Total Score<br>(TS) | Normalized TS<br>(0-100) |
|---------------------|------------|-------------|-------------|-------------|-------------|----------------|-----------------|-----------------|-------------|------------|------------------|------------------|---------------------|--------------------------|
| Apple<br>(AAPL)     | 9→36       | 10→120      | 8→32        | 9→63        | 8→88        | 9→72           | 8→80            | 9→54            | 7→35        | 6→18       | 8→16             | 9→81             | 685                 | 87                       |
| Microsoft<br>(MSFT) | 9→36       | 10→120      | 9→36        | 10→70       | 9→99        | 9→72           | 9→90            | 9→54            | 8→40        | 7→21       | 9→18             | 9→81             | 737                 | 94                       |
| Alphabet<br>(GOOGL) | 10→40      | 10→120      | 9→36        | 9→63        | 9→99        | 8→64           | 8→80            | 10→60           | 8→40        | 7→21       | 10→20            | 10→90            | 734                 | 93                       |
| Amazon<br>(AMZN)    | 8→32       | 9→108       | 7→28        | 8→56        | 8→88        | 7→56           | 7→70            | 8→48            | 7→35        | 6→18       | 8→16             | 8→72             | 655                 | 84                       |
| Meta<br>(META)      | 7→28       | 8→96        | 7→28        | 8→56        | 7→77        | 7→56           | 7→70            | 8→48            | 7→35        | 6→18       | 8→16             | 7→63             | 611                 | 78                       |
| Tesla<br>(TSLA)     | 6→24       | 7→84        | 6→24        | 7→49        | 6→66        | 6→48           | 5→50            | 7→42            | 8→40        | 5→15       | 7→14             | 6→54             | 610                 | 78                       |
| Nvidia<br>(NVDA)    | 10→40      | 9→108       | 9→36        | 9→63        | 8→88        | 8→64           | 8→80            | 10→60           | 9→45        | 6→18       | 10→20            | 10→90            | 712                 | 91                       |

This low-risk tolerant investor, in the top-tier ranks Microsoft, Alphabet, and Nvidia - clear leaders driven by AI and cloud dominance. In the mid-tier she ranks Apple, and Amazon - strong but facing valuation or competitive pressures. In the lower-tier she ranks Meta, and Tesla - innovative but riskier, with weaker fundamentals compared to peers.

A low-risk tolerance Idiosyncratic Investor may justify the assignments for the weights of importance as follows:

- Apple: Strong long-term history, services growth, premium valuation drags P/E.
- Microsoft: AI/cloud leadership, Nadella highly rated, strong forecasts, gaming growth.
- Alphabet: Gemini AI success, strongest 2025 rally, diversified revenue streams.
- Amazon: AWS growth solid, retail margins pressured, competition eroding share.
- Meta: AI diversification promising, FTC victory, but regulatory risks and volatility.
- Tesla: Innovation-heavy (EVs, robots), but volatile, debt-sensitive, valuation stretched.
- Nvidia: AI chip dominance, record revenues, highest score despite valuation risk.

## 5. Usefulness Of Stock Ratings

The investor can use the framework described above to guide her investment decisions. Possible ways to use those results strategically are the following:

**(i) Translate Scores into Portfolio Weighting.** The investor can use the normalized scores to assign proportional weights in her portfolio. For example, if the Normalized Total Scores for the Magnificent Seven are those in the first row of the table below, the investor may assign the weights that appear in the second row of the same table. She can cap lower-scoring stocks or exclude them entirely depending on her risk tolerance.

|                        | Company |      |      |       |      |        |        |
|------------------------|---------|------|------|-------|------|--------|--------|
|                        | MSFT    | NVDA | AAPL | GOOGL | AMZN | META   | TSLA   |
| Normalized Total Score | 94      | 89   | 85   | 78    | 72   | 68     | 62     |
| Suggested Weight       | 25%     | 23%  | 21%  | 18%   | 13%  | 0%-10% | 0%-10% |

**(ii) Define Investment Actions.** The investor can use score bands to guide her buy/hold/sell decisions. For example, here are some possible grade ranges and possible actions:

- (90–100) → Strong Buy / Core Holdings
- (80–89) → Buy / Growth Holdings
- (70–79) → Hold / Watch Closely
- (60–69) → Underweight / Speculative
- (Below 60) → Avoid / Sell

The table in the above section may be modified as follows:

|                        | Company       |      |                 |       |           |             |        |
|------------------------|---------------|------|-----------------|-------|-----------|-------------|--------|
|                        | MSFT          | NVDA | AAPL            | GOOGL | AMZN      | META        | TSLA   |
| Normalized Total Score | 94            | 89   | 85              | 78    | 72        | 68          | 62     |
| Suggested Weight       | 25%           | 23%  | 21%             | 18%   | 13%       | 0%-10%      | 0%-10% |
| Action                 | Core Holdings |      | Growth Holdings |       | Watchlist | Speculative |        |

**(iii) Set Monitoring Triggers.** For each stock, the investor may define what would prompt a re-evaluation:

- Earnings surprises
- Major news (e.g., lawsuits, leadership changes)
- Valuation shifts (P/E ratio spikes or drops)
- Competitor disruption

**(iv) Build a Rebalancing Schedule.** Revisit the scores periodically or after major market events to:

- Adjust weights
- Rotate out of underperformers
- Add new contenders (e.g., emerging AI leaders)

**(v) Layer in Technical Analysis.** It helps refine entry/exit points. Use the grades as a *fundamental base*, then overlay:

- Moving averages (50-day, 200-day)
- Relative Strength Index (RSI) which focuses on *overbought / oversold conditions* [for details see Wilder (1978)]<sup>3</sup>
- Moving Average Convergence Divergence (MACD) which focuses on *trend direction and momentum shifts* [for details see Appel (1979, 2008)]<sup>4</sup>

Together, RSI and MACD, they give a fuller picture: RSI spots extremes in price movement, while MACD confirms whether a trend is strengthening or weakening.

<sup>3</sup> The Relative Strength Index (RSI) is a momentum oscillator developed by Wilder (1978) helps identify whether recent price moves are too extreme, signaling potential reversals. It ranges from 0 to 100 and it signals as follows:  
Above 70 → often considered *overbought* (price may be due for a pullback).  
Below 30 → often considered *oversold* (price may be due for a rebound).

<sup>4</sup> The Moving Average Convergence Divergence (MACD) is a trend-following momentum indicator created by Appel (1979, 2008). It highlights shifts in momentum and confirms trend direction. Its components are [(MACD line = 12-period EMA – 26-period EMA, where EMA=Exponential Moving Average), (Signal line = 9-period EMA of the MACD line), (Histogram = difference between MACD line and signal line.) It signals, Bullish crossover when MACD line rises above signal line and Bearish crossover when MACD line falls below signal line.

**(vi) Create a Watchlist for Lower-Scoring Stocks.** For example, Tesla and Meta scored lower; it does not mean that the investor ought to ignore them. Instead, it pays to track:

- Innovation cycles (e.g., Tesla's new models, Meta's VR/AI progress)
- Debt levels and management changes
- Market sentiment shifts

## 6. Summary & Conclusion

This paper introduces a structured, multi-criteria stock grading system grounded in rationally subjective decision-making principles. The methodology draws from the rational model of decision-making, which emphasizes systematic evaluation of alternatives based on defined objectives and quantifiable criteria [Bazerman & Moore (2012)]. It also incorporates bounded rationality [(Simon (1955)], acknowledging practical constraints in data availability, cognitive processing, and market complexity. For illustration purposes, seven publicly traded technology companies (the Magnificent Seven) were evaluated across many financial dimensions such as, among others, risk, profitability, valuation, growth, dividends, and quality. Each company received a score from 1 to 10 in each category, which was then multiplied by the corresponding weight to produce a weighted sub score. The sum of these sub-scores yielded a Total Score, which was normalized to a 0–100 scale for comparative clarity.<sup>5</sup>

All inputs were point-in-time financial metrics sourced from publicly available data. Scores were assigned based on relative performance within the peer group, with normalization ensuring comparability across dimensions. No forward-looking estimates or analyst opinions were used, reinforcing objectivity and transparency. Weights reflect investor priorities under a rational framework: risk and profitability dominate due to their direct impact on sustainability and return potential, while valuation and growth offer insight into market expectations and expansion capacity. Dividends and quality, though less influential, provide stability and governance signals.

While the present study demonstrates the feasibility of a subjectively rational, weighted multi-criteria framework for stock grading, several avenues remain open for further exploration. First, methodological refinements could be pursued by incorporating alternative weighting schemes such as the Analytic Hierarchy Process (AHP), entropy-based weighting, or machine learning optimization. These approaches may reveal whether dynamic or adaptive weights improve predictive accuracy relative to fixed allocations.

Second, empirical validation across broader contexts is essential. Extending the framework to multiple sectors beyond technology would test its generalizability, while international applications could highlight the impact of differing accounting standards, regulatory environments, and cultural investment norms. Longitudinal back testing across varying market regimes (bull, bear, and transitional phases) would further establish robustness and resilience.

Third, comparative studies against established rating systems such as Seeking Alpha Quant Ratings, Morningstar's Stock Ratings, and Zacks Investment Research could provide insight into the relative strengths and limitations of transparent, rational scoring versus proprietary or analyst-driven models. Such benchmarking would clarify whether transparency and reproducibility confer advantages in investor trust and decision quality.

Finally, integration with decision science and behavioral finance offers a promising frontier. Future work could examine how rational frameworks mitigate common cognitive biases (e.g., anchoring, recency, herd behavior) and whether resource-rational adaptations enhance usability under constraints of limited data and time. Incorporating qualitative dimensions such as governance, environmental, social, and corporate responsibility (ESG) factors may also enrich the model's explanatory power and align it with evolving investor priorities.

Collectively, these directions underscore the potential for a rational, multi-criteria grading methodology not only to advance academic discourse on decision-making in finance but also to provide practical tools for investors seeking transparency, adaptability, and rigor in stock evaluation. Undoubtedly, longitudinal backtesting across broader asset universes (such as the S&P 500 or Dow Jones 30) represents the vital next phase for empirical validation in corporate asset management.

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<sup>5</sup> This approach aligns with Multi-Criteria Decision Analysis (MCDA), particularly the weighted sum model by Keeney & Raiffa, which is widely used in finance and operations research for ranking alternatives under competing objectives.

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