

FROM INDICATORS TO DECISIONS: EVALUATING STOCK SELECTION MODEL COMPLETENESS

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Abstract

In stock selection research, the boundary between technical indicator development and full decision-making model construction is often unclear. Many studies introduce new indicators and present them as models. This paper reviews 22 studies published between 2013 and 2025 to evaluate whether they propose complete decision frameworks or remain at the indicator or selection stage. Three categories are distinguished: (i) indicator or selection papers, which focus on predictive signals without implementation rules; (ii) partial decision-making models, which define some trading logic or portfolio structure but omit key elements such as cost modeling and risk constraints; and (iii) full trading systems, which integrate signals with decision rules and aim to evaluate performance under realistic validation procedures. Using a qualitative classification across seven structural elements, we assess each study's methodological completeness and scope. A concise reporting checklist is proposed to help authors and readers state clearly what is included and what remains beyond the study's scope. The review shows that while many studies define predictive logic, few extend to complete systems with realistic validation or real-time testing. The study contributes a clear framework for distinguishing indicators from decision models and for improving transparency and practical relevance in future research.

Keywords: stock selection, decision making model, technical indicators, trading systems, strategy evaluation.

INTRODUCTION

In stock selection research, a persistent challenge lies in distinguishing between the development of predictive indicators and the construction of full decision-making models. Many recent studies, particularly those using machine learning or alternative data, present return forecasts or stock rankings as if they were complete, deployable trading systems. However, in most cases, essential decision-making components, such as entry and exit rules, risk management, portfolio construction, cost modeling, and validation under realistic trading conditions, are missing. This gap defines the central problem addressed in this study.

As noted by Arnott et al. (2021) and Feng et al. (2020), many data-driven strategies demonstrate strong in-sample

results but fail to incorporate implementation logic or out-of-sample validation, leading to findings that may be misleading or difficult to replicate in practice.

The main goal of this study is to assess the methodological completeness of recent stock-selection research. Specifically, it examines whether published papers define full decision-making frameworks or merely propose predictive signals presented as models. To achieve this, we apply a structured classification framework based on seven essential elements synthesized from theoretical and applied literature on deployable trading system design.

The key contribution is a transparent review and classification scheme that clarifies the actual scope of published work. It includes a practical checklist that helps authors and

reviewers identify whether a study presents a deployable system or remains at the indicator-development stage.

The main limitation of this study lies in its conceptual scope: it evaluates structural completeness rather than empirical performance. Moreover, the classification relies on interpretive judgment, as some studies describe decision logic implicitly rather than explicitly. Nevertheless, the expected outcome is a clearer framework that supports more transparent, consistent, and applicable research in stock-selection modeling.

CONCEPTUAL BASIS FOR EVALUATING DEPLOYABLE STOCK SELECTION MODELS

In stock selection research, it is essential to distinguish between predictive signal development and full decision-model design. While both contribute to quantitative finance, they differ in scope and required structure. This section outlines the theoretical basis for that distinction, defining what makes a model deployable and drawing on insights from replication studies.

A technical indicator typically represents a transformation or summary of market data (e.g., price trends, volume, and volatility) designed to highlight potential trading signals. These indicators can be statistical, rule-based, or derived through machine learning, and they are often used to forecast future returns. However, indicators alone do not form a complete model for decision-making. A decision system takes the additional step of translating such signals into actionable positions, managing associated risks, applying trading constraints, and validating performance under realistic assumptions.

Recent studies often treat predictive accuracy as sufficient, but without defined rules and constraints, such models lack practical relevance. Clear theoretical separation between signals and decision systems is needed to avoid overstated claims and to improve research

transparency.

A deployable decision-making model in finance must account for multiple structural elements that go beyond signal design. Table 1 summarizes seven key components required for a practical system, which also serve as criteria in our classification framework.

When key elements such as trading rules, cost modelling, and validation are missing, the work should be considered an indicator framework. Those that include some decision elements but lack full implementation logic may be termed partial decision-making models.

Research in stock selection often faces methodological and practical challenges that limit its real-world relevance. Many forecasting approaches demonstrate strong results on historical data but lose predictive strength once tested in new periods or under realistic trading assumptions. This usually occurs because models are fine-tuned to past patterns, rely on limited datasets, or omit key implementation factors. Hou et al. (2020) show numerous factor-based strategies lose statistical validity after adjusting for multiple testing and excluding illiquid securities. Similarly, McLean & Pontiff (2016) find that once published strategies become known and arbitrated, their profitability declines substantially. Transaction and market-impact costs further reduce apparent returns, particularly in high-turnover systems (Frazzini, Israel, & Moskowitz, 2018). Short-side performance is even more fragile: when borrowing costs and short-sale constraints are incorporated, most of the reported excess returns disappear (Muravyev, Pearson, & Pollet, 2025). These findings indicate that evaluating models should prioritize their reliability and real-world applicability, rather than relying solely on predictive accuracy.

Based on these insights, this study proposes a structured approach to classify stock selection research by how fully each study defines and supports a usable trading system. Specifically, it distinguishes

between three types of contributions: (i) indicator or selection studies, which focus on predictive signals without implementation rules; (ii) partial decision-making models, which include some trade logic or portfolio construction but lack cost modelling, risk controls, or comprehensive validation; and (iii) full trading systems, which integrate most structural components

and evaluate them under realistic trading assumptions and validation procedures. This approach enhances clarity and comparability in financial research, helping both authors and readers assess how completely a given study defines a practically deployable decision-making framework.

1 table. Core Elements and Evaluation Criteria for Deployable Stock-Selection Models

Element	Description	Why it matters
Signal construction	Preparation of input data, including correction of errors, conversion to usable formats, and time alignment to prevent bias.	Ensures transparency, reproducibility, and minimizes data-snooping bias in model design (Hou et al., 2020; Gu et al., 2020).
Entry/Exit logic	Explicit rules for initiating and closing positions	Defines how predictive signals are operationalized into actual trading decisions, a key step in bridging theory and implementation (Fischer & Krauss, 2018; Yang et al., 2020).
Position sizing	Capital allocation rules across assets	Determines exposure and diversification, directly affecting the portfolio's risk-return profile (Novy-Marx & Velikov, 2016).
Risk constraints	Exposure limits, drawdown control, volatility targeting	Prevents excessive leverage and instability in strategy performance, enhancing capital preservation (Théate & Ernst, 2021; Yang et al., 2020).
Trading costs & liquidity	Assumptions about spreads, impact, execution delay	Introduces realism into performance estimation, as ignoring costs often leads to overstated returns (Frazzini et al., 2018; Detzel, Novy-Marx, and Velikov, 2023).
Shorting constraints (conditional)	Borrow availability, fees	Determines the real-world feasibility of short-selling trades and explains the frequent fragility of short-side profitability (Muravyev et al., 2025; McLean & Pontiff, 2016).
Validation and reliability	Out-of-Sample testing, Walk-forward Cross-validation, overfitting diagnostics and when available live or paper-trading evaluation	Determines whether the strategy performs consistently on unseen data and under real trading conditions; statistical validation indicates near-deployable full trading system, while live testing confirms fully deployable system (Bailey et al., 2017; Sweet et al., 2023).

Source: created by authors based on scientific literature (2025).

METHODOLOGY

In this study we apply a structured qualitative review to evaluate how recent literature in stock selection research differentiates between technical indicator development and complete decision-making model construction. The goal is to identify whether a given study provides a full decision framework that can be directly implemented in trading environments, or whether it primarily introduces a new indicator or signal without the

complementary decision components.

The research follows a multi-stage approach. First, relevant academic papers were identified using established databases such as Scopus, Web of Science, Research Gate, and Science Direct. The search covered the period 2013-2025 to capture contemporary developments in data-driven and algorithmic finance. The keywords included “stock selection”, “technical indicator”, “stock decision making model”, “trading strategy”, “stock selection

system”, “trading systems”. Only peer-reviewed journal articles and working papers with full methodological sections were included.

Selection criteria: relevant studies on stock selection and decision-making models were identified through a structured screening process. Inclusion required that each paper (1) present a stock selection or signal-generation approach, (2) apply quantitatively defined methods, and (3) provide enough methodological detail to assess whether decision elements such as entry/exit rules, validation, or cost modeling were included. Both traditional financial and machine-learning-based models were considered.

From the reviewed literature, 22 studies were selected for detailed classification. For each, methodological information was extracted, which covers signal design, decision logic, and treatment of trading constraints in order to enable consistent comparison and synthesis of how each study contributes to stock selection model development.

Quality assessment (classification framework): each study was evaluated using a classification framework derived from the theoretical structure outlined in Section 2. The framework distinguishes between three conceptual categories:

(a) Indicator development – studies that introduce or modify a technical indicator or predictive signal but do not define trading or decision rules.

(b) Decision-making model – studies defining explicit or partial decision logic (e.g., entry or exit rules, portfolio creation, or risk filters) but may omit full operational details.

(c) Full near-deployable or deployable trading system – studies that integrate signal generation, decision rules, risk control, transaction costs, and validation under realistic or live trading conditions. Statistical out-of-sample validation indicates a near-deployable model, while confirmed live or paper-trading results indicate a fully deployable system.

Each publication was assessed across seven structural dimensions: (1) Signal construction, (2) Entry/exit rules, (3) Position sizing, (4) Risk constraints, (5) Trading frictions, (6) Shorting constraints (conditional), and (7) Validation practices.

The presence or absence of each element was coded as 1 (present) or 0 (absent), enabling transparent comparison. Studies with most elements absent were classified as indicator-focused; those with partial coverage as decision-making models; and those with nearly all elements, including thorough validation, as deployable or fully deployable systems.

Synthesis of findings: classification results were summarized to identify recent trends in stock-selection research – how many studies remain at the indicator or selection level, how many define partial models, and how few approach deployable system design. When uncertainty arose – for instance, when trade rules were implied but not explicitly stated – an intermediate score was assigned.

RESULTS AND DISCUSSION

Our findings indicate that the majority of studies focus on indicator development or signal-based selection methods. Specifically:

11 out of 22 studies were classified as indicator/selection only, meaning they propose predictive signals or ranking methods without defining trading execution rules, portfolio construction, or real-world constraints.

8 out of 22 were identified as partial decision-making models, incorporating some trading logic but omitting key elements such as cost modeling, risk budgeting, or validation.

3 out of 22 approach the level of a full decision system, evaluating their models under realistic trading conditions, including transaction costs, liquidity constraints, or turnover limits.

These proportions reflect the composition of our selected sample and should not be interpreted as definitive of the

broader literature. A more strategy-focused inclusion process might yield a higher share of full models. Nevertheless, the result highlights a consistent gap between prediction-focused contributions and models prepared for implementation.

Examples of indicator/selection studies include:

Indicator or Selection-Level Studies

Gu et al. (2020) use machine learning to predict stock returns from a large set of firm characteristics. Their forecasts show strong out-of-sample performance, but the study ends at prediction and does not address trading costs, execution, or risk limits.

Drobetz & Otto (2021) apply similar ML techniques to European markets, testing predictive accuracy across assets and periods. They report portfolio returns and risk metrics but do not specify trading rules, cost assumptions, or portfolio constraints.

Studies of Tan et al. (2019), Saetia et al., Ghosh et al. (2021), and Sharma & Bhalla (2025) also contribute valuable advances in predictive modeling and indicator design, offering useful insights for signal generation and market analysis, yet they remain primarily at the indicator-development stage without full specification of trading execution, risk management, or validation under real trading conditions.

Decision-Making Models

Berouaga et al. (2023) created a system which defines portfolio construction and rebalancing logic but omits trading-cost modeling and realistic validation.

Brito (2023) introduces a stock-selection model combining expected utility, entropy, and variance to rank and preselect assets for mean-variance optimization. The system defines clear selection logic but lacks trading-cost modeling and out-of-sample validation.

Full trading systems (Deployable and nearly-deployable trading models)

Goumatianos et al. (2013) present long-short trading model using intraday pattern recognition and technical indicators. The

model defines explicit entry/exit rules, dynamic portfolio weighting, and includes transaction-cost and out-of-sample testing, demonstrating practical application.

Mosina & Žilinskij (2025) implement a simplified pairs-trading system tested in real time. The strategy defines all decision components - signal, entry/exit, risk limits, costs, and shorting feasibility, and validates results under actual trading conditions, so it qualifies as a fully deployable trading model.

Théate & Ernst (2021) - very close to a deployable prototype: defines all key components (entry/exit, costs, position sizing, and evaluation). However, relies on simulated order execution.

Yang et al. (2020) developed a trading framework that specifies entry and exit logic, position sizing, and transaction-cost modeling. The system is validated with out-of-sample and walk-forward tests, showing stable simulated returns under realistic assumptions. Although the model covers all structural elements, its validation remains statistical rather than live, making it a nearly deployable trading system under the classification scheme.

Across all reviewed studies sizing methods are often simplified. Explicit risk budgeting is rare. Cost modeling, liquidity screens, and realistic validation are the most commonly missing components. Where these are included, results tend to be more conservative and model rankings often shift, reinforcing the importance of full-system evaluation. For example, Detzel et al. (2023) re-examine leading asset-pricing models under realistic transaction-cost assumptions, showing that model rankings and implied performance change substantially once costs are included. Frazzini et al. (2018) estimate realized trading costs across a wide range of equity strategies and firm sizes. The study quantifies how spreads, impact, and turnover erode apparent alpha and offers one of the most detailed empirical mappings of cost effects in institutional trading data. Novy-Marx & Velikov (2016)

provide taxonomy of anomalies with explicit modeling of trading costs and turnover. Their findings show that many reported factor returns disappear once trading frictions are considered, highlighting the need for cost and capacity awareness in model evaluation.

These observations confirm the study's main point: many recent works remain at the signal or partial-model stage. Clearer classification, consistent terminology, and fuller modeling frameworks are key to bridging the gap between research and implementation.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

This review examined how recent stock-selection studies present their contributions and implement their strategies: as predictive indicators or as full decision-making systems. We found that many focus on signal generation without extending to execution logic, risk management, or validation under realistic trading conditions.

Rather than measure this pattern, we emphasize the importance of methodological completeness for future research. A predictive signal becomes practically useful only when integrated into a full system—with defined trade rules, cost modeling, and thorough evaluation.

We propose a structured classification and reporting checklist to help authors and reviewers communicate clearly whether a study presents a deployable model or stops at signal-level exploration. Future research would benefit from shared test sets, transparent examples of full-model design, and more consistent inclusion of trading frictions, portfolio logic, and real-time trading constraints.

These steps can improve clarity, comparability, and ultimately, the practical relevance of research in stock selection and equity trading. Strengthening methodological standards will help bridge the gap between academic innovation and real-world application, ensuring that future

models evolve from predictive concepts into fully implementable decision frameworks.

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