The American Journal of Management and Economics Innovations
ISSN 2693-0811 | Open Access

TYPE Original Research
PAGE NO. 128-137
DOI 10.37547/tajmei/Volume07Issue08-11

Check for updates

Algorithmic Trading + Behavioral Finance

Maksim Baradziuk
Independent Algorithmic Trading Consultant and Quantitative Researcher serving international financial institutions Los Angeles, USA

OPEN ACCESS
SUBMITTED 31 July 2025
ACCEPTED 08 August 2025
PUBLISHED 21 August 2025
VOLUME Vol.07 Issue 08 2025

CITATION
Maksim Baradziuk. (2025). Algorithmic Trading + Behavioral Finance. The American Journal of Management and Economics Innovations, 7(8), 128–137. https://doi.org/10.37547/tajmei/Volume07Issue08-11

COPYRIGHT
© 2025 Original content from this work may be used under the terms of the creative commons attributes 4.0 License.

Abstract: The study is devoted to identifying and analyzing the synergistic interaction between the theoretical principles of behavioral finance and applied methodologies for developing high-r eturn algorithmic strategies in the digital asset segment. In conditions where the efficient market hypothesis demonstrates limitations in its applicability, especially in environments with increased volatility and underdeveloped infrastructure—such as cryptocurrency markets and decentralized finance (DeFi) ecosystems—behavioral biases emerge as important determinants of market inefficiency. The paper presents a framework that combines the targeted exploitation of cognitive patterns, including the disposition effect and the phenomenon of herd behavior, with the application of advanced technological solutions. Based on four original case studies—ranging from the development of a proprietary backtesting mechanism incorporating elements of chaotic process modeling to the construction of a predictive risk management system for DeFi—the practical implementation of the proposed approach is demonstrated. The results obtained confirm the superiority of the hybrid architecture over traditional methods: from effectively reducing crash risk in DeFi carry trade strategies to maintaining portfolio resilience under market stress conditions and generating ultra-high returns (CAGR exceeding 200% with MDD of 30%). The study's findings reinforce the validity of the adaptive markets hypothesis and confirm the applied value of the synthetic methodology for modern algorithmic trading. The information reflected in the study will be of interest to asset managers, quantitative fund specialists, and researchers focused on creating next-generation algorithms.

Keywords: algorithmic trading, behavioral finance, prospect theory, herd behavior, risk management,

decentralized finance (DeFi), backtesting, chaos modeling, portfolio rebalancing, cryptocurrencies.

Introduction

The modern architecture of financial markets is shaped by the influence of two interconnected yet seemingly opposite megatrends. On the one hand, there is the intensive development of algorithmic trading, artificial intelligence (AI), and machine learning (ML) methods, which enable the processing and interpretation of vast arrays of market information with unprecedented speed and accuracy. On the other hand, there is a growing interest within the research community in behavioral finance, which challenges the universality of the Efficient Market Hypothesis (EMH) and demonstrates that investors' cognitive biases influence the price formation process. This methodological dualism is most clearly manifested in environments with a high degree of uncertainty and volatility, such as decentralized finance (DeFi). In 2024, the DeFi market volume was estimated at USD 21.04 billion, with a projected increase from USD 32.36 billion in 2025 to approximately USD 1,558.15 billion by 2034, reflecting average annual growth of approximately 523.9% over the 2025-2034 period [19]. Such dynamics simultaneously create unique opportunities for generating excess returns and shape an unprecedented spectrum of risks.

The behavioral paradigm acquires particular significance in relation to digital financial ecosystems. The cryptocurrency and DeFi segments, characterized by the dominance of retail participants, extreme price volatility, and the absence of generally accepted fundamental valuation models, constitute a fertile ground for the amplification of irrational behavioral factors. Common phenomena such as fear of missing out (FOMO), panic reactions to destructive rumors (FUD), and the pronounced dependence of market sentiment on social media information flows contribute to the manifestation of herd behavior and the disposition effect [5]. Under such conditions, traditional financial models often demonstrate methodological vulnerability, while behavioral concepts find convincing empirical support.

The aim of the study is to develop and theoretically substantiate an integrated framework for the design and operation of high-yield algorithmic trading strategies. This framework assumes the synthesis of behavioral finance principles, aimed at identifying and exploiting market anomalies, with advanced approaches to modeling chaotic dynamics and managing specific risks inherent in digital assets.

To achieve this aim, the following **objectives** are defined:

- to systematize the main behavioral anomalies characteristic of digital assets, based on prospect theory and the concept of herd behavior;

- to analyze the methodological limitations of classical backtesting approaches and to propose an improved model that accounts for the nonlinear and chaotic properties of the market, thereby enhancing the robustness of algorithms;

- to propose a conceptual model of dynamic risk management for carry trade strategies in the DeFi ecosystem, ensuring proactive responses to the deterioration of collateral asset quality;

- to demonstrate, using proprietary case studies, the practical implementation and empirical effectiveness of the integration framework.

The scientific novelty of the study lies in the comprehensive synthesis of theoretical-behavioral approaches with proprietary engineering solutions in the field of algorithmic trading.

The research hypothesis is that the systematic exploitation of market inefficiencies caused by behavioral anomalies (in particular herd behavior and the disposition effect), combined with engineering solutions that model the chaotic nature of the market and implement preventive management of specific risks associated with digital assets, makes it possible to develop algorithmic trading strategies with consistently high, statistically significant, and risk-adjusted returns that exceed the performance of both traditional benchmarks and strategies based solely on classical financial models.

Materials and Methods

Behavioral finance forms the methodological foundation for interpreting market anomalies and developing algorithms that account for the behavioral specifics of participants. Kumar N.C. [1] integrates key cognitive biases—overconfidence, loss aversion, and anchoring—considering them as determinants of persistent inefficiencies and as a basis for parameterizing trading strategies. Empirical verification at the micro level is reinforced by the findings of Gabhane D., Sharma A., Mukherjee R. [2], demonstrating that availability and representativeness heuristics manifest in the rhythm of trading activity and the propensity for risk-seeking. In the logic of this vector, Reddy K. et al. [3] quantitatively record the correlation between individual biases (herding, recency effect) and stock selection, proposing metrics suitable for direct integration into algorithmic trading pipelines. Mehraj K., Kumar V. [4] create an applied typology of psychological errors and identify transactional vulnerability nodes where behavioral filtering demonstrates the highest efficiency. At the conceptual level, Liu Y. Y. et al. [8] confirm the relevance of cumulative prospect theory for online trading. Prashanth L. A. et al. [9] integrate cumulative prospect theory with reinforcement learning methods, building a formalism in which the investor's utility function, with asymmetry in the loss domain, becomes part of the strategy optimization criterion.

Herding behavior serves as a key link between individual cognitive biases and macroeconomic market effects. Mavruk T. [10] applies machine learning methods to identify portfolio clusters of synchronous actions by retail investors, highlighting heterogeneity in terms of experience and turnover. Choijil E. et al. [11], through bibliometric analysis, cover a thirty-year period of research agenda evolution, recording a shift from primitive congruence metrics to complex network and causal models.

The sphere of cryptocurrencies and DeFi brings behavioral mechanisms to the forefront under conditions of thin order books and information cascades. Bennett D., Mekelburg E., Williams T. H. [5] propose the concept of BeFi meets DeFi—a pricing model for decentralized assets where yield parameters are determined by behavioral liquidity and network effects. Sundarasen S., Saleem F. [6] systematize and bibliometrically analyze studies on the influence of social media on cryptocurrency markets, reconstructing the topology of signal transmission from publications to transactions. Risk management in DeFi is reinterpreted through the lens of XAI and on-chain transparency: Rkein H., Danach K., Rachini A. [12] demonstrate how explainable models and smart contract audits allow ranking protocols by risk profile.Weingärtner T. et al. [13] create a visualized mapping of vulnerabilities (oracle risks, liquidation mechanisms, inter-protocol dependencies) for real-time monitoring of systemic fragility. Source [19] provides statistics on changes in the size of the decentralized finance market, as well as estimates of its share and development trends for 2025–2034.

Algorithmic trading increasingly uses generative and interactive simulation environments capable of incorporating behavioral endogeneity. Coletta A. et al. [14] apply GANs to construct realistic market simulations that reproduce both stylized facts and rare events. Yao Z. et al. [15] train reinforcement learning agents in multi-agent environments, demonstrating that coevolution of strategies induces endogenous volatility and return autocorrelations. In the applied ML domain, Peng Y. L., Lee W. P. [17] formalize an intraday data selection procedure for currency trading to minimize overfitting, paying particular attention to the temporal representativeness of samples. Goldblum M. et al. [18] emphasize the threat of targeted and transfer-based adversarial attacks on high-frequency trading models.

A separate axis of discussion is formed by questions of data quality, replicability, and proper evaluation infrastructure. Owens E. et al. [7] adapt the FAIR principles to the financial context (FAAIR), formulating requirements for data findability, accessibility, interoperability, and reusability, which are essential for reliable model calibration and backtesting. Palomar D.P. [16] lists the main methodological errors (data snooping, excessive factor parameterization, look-ahead bias, survivorship bias) and proposes mechanisms for their prevention.

Taken together, this body of research demonstrates the convergence of three directions: the translation of behavioral mechanisms (from CPT to the herding effect) into operationalizable features and constraints; the development of simulation and RL/generative platforms as a testing ground for analyzing endogenously formed market patterns; and the institutionalization of data protocols, validation, and evaluation metrics to ensure proper strategy verification. At the same time, substantive gaps remain. First, models with behavioral preferences [8, 9] rarely reach the stage of industrial implementation, while applied ML developments [17] often ignore endogenous feedback from strategy to market, which contradicts conclusions from agent-based simulations. Second, several DeFi studies [5, 6] emphasize the dominance of social signals, while XAI-based risk management frameworks [12, 13] are built on the assumption of quasi-stationary identifiability of risk factors—this contradiction has not yet been resolved. Third, industry standards for working with data and metrics [7, 16] imply strict backtesting regulations, whereas empirical studies of herding and crypto risks often rely on non-replicable datasets or heuristic labels (as directly indicated in source [10]).

Results and Discussion

The main difference between the classical and behavioral approaches in financial theory lies in the interpretation of market participants' rationality. Within the framework of the classical paradigm, it is assumed that the investor acts based on the task of maximizing expected utility. In contrast, behavioral theory asserts that cognitive and emotional features of the human psyche systematically and predictably distort the decision-making process. The most significant conceptual constructs explaining a wide range of market behavior anomalies are prospect theory and the herding phenomenon.

Prospect theory, developed by Prashanth L. A. et al. [9], formalizes the patterns of decision-making under conditions of uncertainty and risk. The central propositions, repeatedly confirmed by experimental studies, include:

- evaluation relative to a reference point. Individuals perceive financial outcomes not in absolute levels of wealth but as gains or losses relative to a specific reference point (often the purchase price of an asset);

- asymmetry in the perception of losses and gains (Loss Aversion). The subjective value curve is asymmetric: the psychological discomfort from a loss is approximately twice as intense as the emotional satisfaction from an equal gain in absolute value;

- reflection effect. This asymmetry shapes opposing attitudes toward risk depending on the context: in the domain of potential gains, investors tend to exhibit risk aversion, preferring a guaranteed smaller return over an uncertain larger one; conversely, in the loss domain, they often choose risky strategies in an attempt to avoid realizing losses [8].

One of the most well-known practical manifestations of prospect theory in investment activity is the disposition effect. It is expressed in a persistent behavioral pattern: the premature realization of gains on appreciating assets and excessively prolonged holding of losing positions in anticipation of a price return to the breakeven point [4]. A large-scale study of transactions has shown that the median holding period for losing assets significantly exceeds the corresponding indicator for profitable ones. This deviation from the rational model, driven by the loss aversion phenomenon, is one of the key reasons for capital reduction among a significant portion of market participants [8].

The second systemic element among behavioral anomalies is herding behavior. It describes the tendency of investors to ignore their own informational signals and follow the collective actions of the majority. Such dynamics may have a rational nature, for example, in the form of an information cascade, when it is assumed that the aggregated knowledge of the group surpasses that of the individual. However, it is often based on irrational emotional impulses: the fear of missing out on a general movement (FOMO) or panic reactions to adverse events.

In financial markets, the phenomenon of herding behavior is one of the factors contributing to the formation of speculative bubbles and subsequent sharp price crashes. This mechanism amplifies existing price trends, increases the degree of correlation between different assets during periods of turbulence, and leads to the emergence of so-called heavy tails in return distributions, in which extreme fluctuations occur much more frequently than predicted by the normal distribution [11]. In recent years, machine learning methods have been increasingly used to detect and quantitatively assess manifestations of herding behavior based on market data analysis, opening up opportunities for its targeted algorithmic exploitation [10].

It should be emphasized that prospect theory and herd behavior are not isolated phenomena. Under conditions of market turmoil, they engage in mutual reinforcement, forming a positive feedback loop capable of leading to large-scale crashes. An initial price shock triggered by a negative informational impulse often sets off a chain of sell-offs. This process activates the herd mechanism: observing the decline in quotations, investors begin to sell assets solely because other market participants are doing the same, thereby intensifying downward price pressure. Asset holders who find themselves in the loss zone according to the prospect theory scale, due to an increased propensity for risk, tend to hold their positions in the hope of a trend reversal, effectively providing liquidity for the exit of the main body of sellers. However, as psychological pressure mounts and losses accumulate, the stage of mass capitulation occurs, when asset sell-offs take place at the price minimum, cementing the final and most destructive phase of the collapse.

The classical methodology for testing trading algorithms—backtesting—is based on simulating the operation of a strategy on historical data. Despite its prevalence, this approach suffers from a fundamental limitation: it assumes that the market is a static exogenous environment on which the tested strategy exerts no feedback effect. Such an assumption ignores the reflexive nature of financial markets—the ability of participants, through their actions, to modify price dynamics, forming complex closed feedback loops [14]. As a result, fragile trading solutions are created, optimized for specific historical conditions but lacking resilience to structural shifts in the market environment and unpredictable shocks.

The most appropriate theoretical basis for analyzing the functioning of modern highly volatile and speculative markets is the concept of complex adaptive systems. Such systems exhibit properties characteristic of deterministic chaos: high sensitivity to initial conditions (the butterfly effect), pronounced nonlinearity, and fractal organization of time series. The study of such systems requires the use of models that go beyond traditional statistical methods based on the hypothesis of a normal distribution of random variables [1, 14].

Further in the study, case studies will be presented that clearly demonstrate the capabilities and effectiveness of the proposed analytical approach.

Case Study 1: Architectural Principles of Developing a Proprietary Backtesting Engine.

The limitations inherent to classical backtesting methodologies became the primary incentive for creating a specialized proprietary software core designed for testing and optimizing algorithmic strategies. Unlike the standard approach, which assumes a single run of a strategy on retrospective price quotes, the developed engine uses historical data only as a starting point for synthesizing an ensemble of simulation trajectories of possible market dynamics. Conceptually, this method correlates with hybrid models of the Chaos–Markov–Gaussian class, aimed at simultaneously capturing deterministic chaotic patterns and stochastic switches between different market regimes.

The key objective of such a simulation architecture is not to predict a specific trajectory of future prices, but to conduct systematic stress testing of the algorithm across a spectrum of statistically plausible yet potentially adverse scenarios. A strategy can be considered robust if, within the entire generated ensemble, it demonstrates satisfactory averaged performance metrics (for example, Sortino ratio that is above targeted benchmark), and not only on a single favorable historical sample [14, 15].

A comparative description of various backtesting paradigms is presented in Table 1.

Table 1. Comparative analysis of backtesting paradigms (compiled by the author based on [14, 15]).

Characteristic	Traditional Backtesting	Agent-Based Modeling (ABM)	Proprietary Engine (Chaos Modeling)
Market Impact Modeling	Absent. The market is considered an unchanged external factor.	High. Impact is modeled through direct interaction of agents with the order book.	Partial. Modeled through stochastic shocks in volatility and liquidity.
Reflexivity and Feedback Loops	Not considered.	A key property. Agent behavior adapts to the actions of others.	Implicitly accounted for through the generation of multiple nonlinear scenarios.

Emergent Behavior	Impossible.	The main goal is to reproduce macro-phenomena (crashes, bubbles) from micro-rules.	Not directly modeled, but the system tests resilience to it.
Implementation Complexity	Low. Standard tools are widely available.	Very high. Requires calibration of multiple agents and significant computation.	Medium. Requires development of a proprietary scenario generator.
Main Objective	Maximization of historical performance.	Explanation and understanding of market mechanisms.	Maximization of robustness and strategy resilience to future uncertainty.

The decentralized finance (DeFi) ecosystem, possessing significant innovative potential, is simultaneously characterized by a spectrum of specific risks that have no direct analogs in the traditional financial environment. In addition to typical market threats, such as price fluctuations and changes in interest rates, participants face technological challenges: vulnerabilities in the source code of smart contracts, errors or manipulations by oracles (external data providers), as well as risks of hidden or explicit centralization in protocol governance mechanisms. For lending platforms and automated market makers (AMM), economic threats, including impermanent loss and cascading liquidations of collateralized positions, acquire particular importance [13]. Effective functioning under such conditions presupposes the application of integrated approaches that combine traditional financial analysis with a detailed understanding of the architectural and algorithmic features of specific protocols [12].

Carry trade strategies in the DeFi space, which are often implemented through staking or providing liquidity in high-yield pools, bear the full set of risks inherent to classical carry trade operations, including the danger of a sharp price collapse (crash risk). In the context of DeFi, this threat is exacerbated by heightened sensitivity to the quality of collateral assets: yield is generated in one token, while the collateral is represented by another, often more volatile and less liquid instrument. A sharp loss of confidence in such a collateral asset can trigger a rapid collapse of the entire system, which has been repeatedly confirmed in the real history of DeFi development.

Case Study 2: Proprietary Risk Management Model for Carry Trade in DeFi. Within a division engaged in digital asset management in the DeFi ecosystem, a proprietary dynamic risk management model was developed, designed to address complex multifactor threats. A distinctive feature of this model lies in shifting the focus from the reactive approach typical of classical stop-loss mechanisms to predictive analysis. Instead of recording a loss after the fact, the algorithm is aimed at forecasting the deterioration of the fundamental "health" indicators of the underlying assets serving as collateral or sources of yield.

The model operates in continuous monitoring mode and processes heterogeneous data streams:

- on-chain indicators: transaction activity dynamics, trading volume on DEXs, changes in total value locked (TVL), distribution of tokens among large holders (whales);

- market information: price levels, as well as realized and implied volatility;

- qualitative characteristics of protocols: availability of recent security audit reports and their results, developer activity, community discussions [2, 3].

The integration of these parameters is carried out by forming a composite reliability index for each asset and protocol in the portfolio. If this indicator falls below a set critical threshold, the system initiates an adaptive risk reduction procedure. This process may include partial or complete position liquidation, withdrawal of liquidity from a pool, or the establishment of hedging instruments. It is fundamentally important that the activation of this mechanism occurs before market turbulence or a vulnerability disclosure triggers a sharp price drop, thereby providing the strategy with a critical time advantage. The structural diagram of the model is presented in Figure 1.

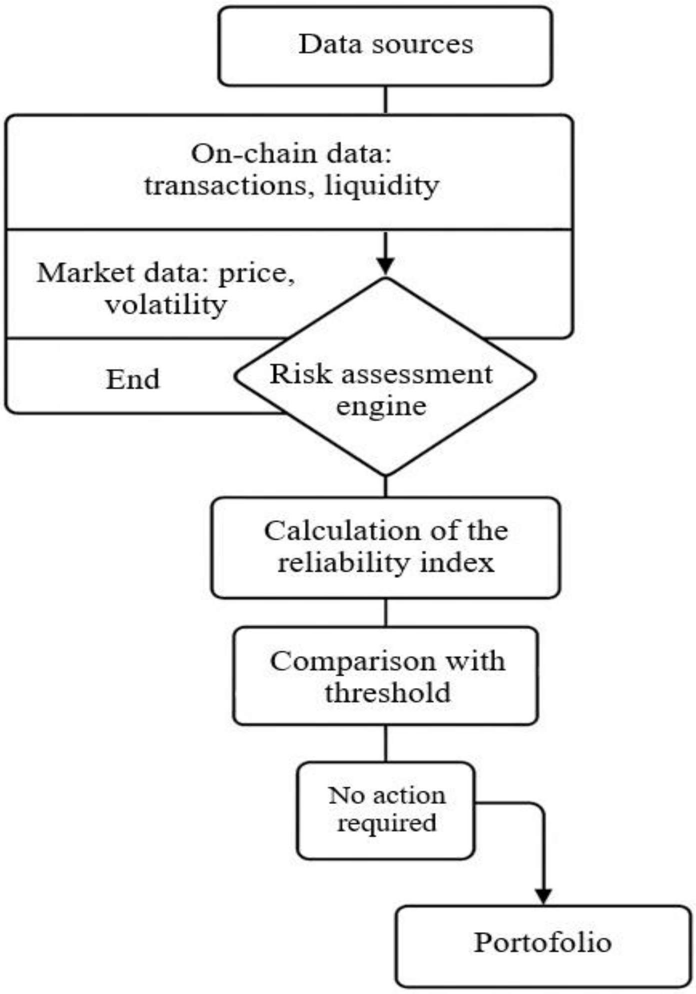

Fig. 1. Architecture diagram of the dynamic DeFi risk model (compiled by the author based on [3, 6, 18]).

The approaches presented above — the use of behavioral anomalies, the implementation of robust testing, and predictive risk management — do not exist in isolation from one another. Their maximum effectiveness is revealed within the framework of integrative interaction, in which a unified analytical and managerial framework is formed, ensuring the stable operation of trading systems even under conditions of extreme market turbulence.

Case Study 3: Rebalancing During the FTX Collapse. The practical effectiveness of this method was vividly demonstrated in the process of managing the investment portfolio of a large private family office. The collapse of the cryptocurrency exchange FTX acted as a catalyst for large-scale market panic and a chain reaction of sell-offs, clearly illustrating the mechanics of herd behavior among market participants. In response to these events, the company implemented its internally developed rebalancing strategy, which was based not on fixed calendar periods but on predetermined threshold levels and market volatility indicators.

The approach was founded on a systematic application of countercyclical logic: assets relatively resilient to the shock were sold, while securities subjected to the greatest price pressure due to irrational panic were simultaneously acquired [3, 7]. This mechanism not only helped to mitigate the negative impact of falling quotations but also created a foundation for portfolio value recovery by purchasing fundamentally robust assets at prices significantly below their fair value.

Case Study 4: Flagship Ultra-High Yield Strategy. The final stage of the research and applied work was the development of a flagship trading model integrating the entire previously presented analytical and methodological toolkit. The conceptual basis of the strategy lies in the deliberate utilization of behavioral anomalies among market participants. The model systematically identifies and exploits persistent momentum movements, often arising as a result of emerging herd behavior. In parallel, it identifies zones of extreme pessimism and market panic, opening countertrend positions at calculated moments of probable price reversals, predictable within the framework of prospect theory.

The development, testing, and calibration of the algorithmic architecture of the strategy were carried out using the author's backtesting module, capable of modeling the chaotic dynamics of the market. This methodology ensured high structural stability (robustness) of the model and minimized the risk of overfitting.

Empirical results of the strategy's application over a two-year period demonstrate its outstanding efficiency. The compound annual growth rate (CAGR) over two consecutive years exceeded 200%, while the maximum drawdown (MDD) remained below 30%. Recognizing that the CAGR and MDD indicators represent simplified and incomplete measures of performance, an in-depth analysis based on risk-adjusted metrics was conducted. As shown in Table 2, the strategy demonstrates significantly higher Sharpe and Sortino ratios compared to benchmark assets, indicating that its exceptional profitability results from effective risk control and allocation rather than mere compensation for elevated risk levels.

Table 2. Key performance indicators (KPI) of the author's strategy (2022-2023) (compiled by the author based on [3, 6, 16, 17]).

Metric	Proprietary Strategy	Bitcoin (Buy & Hold)	S&P 500 (Buy & Hold)
CAGR	> 200%	≈ 58%	≈ 11%
Maximum Drawdown (MDD)	< 30%	≈ 75%	≈ 25%
Volatility (St.Dev, annual)	≈ 60%	≈ 80%	≈ 20%
Sharpe Ratio	> 2.0	≈ 0.47	≈ 0.33
Sortino Ratio	> 5.0	≈ 1.0	≈ 0.7

The cumulative return chart (Fig. 2) clearly demonstrates the extent of the strategy's outperformance compared to market benchmarks.

Fig. 2. Total return on a logarithmic scale (Start = 100) (compiled by the author based on [3, 6, 16, 17]).

The study demonstrated that a combination of behavioral factors, robust testing, and predictive risk management significantly enhances the resilience and performance of trading systems under conditions of high turbulence. Prospect theory and the phenomenon of herd behavior not only explain the nature of market anomalies and crisis scenarios but can also serve as a basis for strategies that capitalize on both momentum trends and countertrend situations. The solutions described in the study enable adaptive responses to risks and structural market changes, providing a temporary advantage.

The empirical results of the flagship strategy confirmed its ability to deliver high returns with a controlled level of risk, as reflected in a significant outperformance in the Sharpe, Sortino, and Calmar ratios compared to benchmarks. This efficiency was achieved through the integration of analytical, technological, and behavioral tools into a unified management framework, which forms the foundation for long-term competitiveness and resilience in a dynamic financial environment.

Conclusion

The conducted study convincingly demonstrates that market anomalies driven by behavioral and cognitive biases of participants are not an abstract theoretical hypothesis but an objectively reproducible and systematically exploitable source of alpha generation, particularly in the context of emerging and highly volatile segments of the digital asset market. Nevertheless, extracting sustainable profit from such inefficiencies is impossible through traditional quantitative analysis tools and requires a profound transformation of the paradigm of design, testing, and risk management of algorithmic trading systems.

The conceptual and applied framework proposed in this study has practical value for a wide range of professional financial market participants: from asset managers and quantitative hedge funds to individual investors specializing in trading cryptocurrencies and related derivatives.

The prospects for further research lie in the direction of increasing complexity and representativeness of simulation models. Special attention should be given to the development of Agent-Based Models, which make it possible to interpret market dynamics not as an impersonal stochastic process but as an emergent result of interactions among a multitude of heterogeneous agents differing in goals, strategies, and psychological attitudes. Additionally, the integration of Natural Language Processing (NLP) technologies for the prompt analysis of sentiment in social media and news flows may provide more sensitive and anticipatory indicators of herd behavior formation, which in the future could enhance the predictive power and adaptability of algorithmic strategies.

References

1. Kumar N.C. The Significance of Behavioral Finance inComprehending Market Anomalies // International Journal of Modern Science and Research Technology. - 2025. - Vol. 3 (5) - pp. 422-434. https://doi.org/10.5281/zenodo.15532209.

2. Gabhane D., Sharma A., Mukherjee R. Behavioral finance: exploring the influence of cognitive biases on investment decisions //Boletin de Literatura Oral-The Literary Journal. – 2023. – Vol. 10. – pp. 3133-3141.

3. Reddy K. et al. Cognitive Biases and Investor Behavior: A Behavioral Finance Perspective on Stock Market Investment Decisions //International Journal of Environmental Sciences. – 2025. – Vol. 11 (3). – pp. 1-8.

4. Mehraj K., Kumar V. Psychological Biases in Investment Decisions: A Behavioral Finance Approach. – 2025.- pp. 1-9. https://doi.org/10.20944/preprints202502.2000.v1 .

5. Bennett D., Mekelburg E., Williams T. H. BeFi meets DeFi: A behavioral finance approach to decentralized finance asset pricing //Research in International Business and Finance. – 2023. – Vol. 65. – pp. 1-18. https://doi.org/10.1016/j.ribaf.2023.101939.

6. Sundarasen S., Saleem F. From Tweets to Trades: A Bibliometric and Systematic Review of Social Media's Influence on Cryptocurrency //International Journal of Financial Studies. – 2025. – Vol. 13 (2). – pp. 1-18. https://doi.org/10.3390/ijfs13020087.

7. Owens E. et al. On the transposition of FAIR Data Principles to Financial Services: An adapted FAAIR guideline //Accounting, Finance & Governance Review. – 2025. – Vol. 34. - pp. 1-38 https://doi.org/10.52399/001c.138720.

8. Liu Y. Y. et al. Prospect theory for online financial

trading //PloS one. – 2014. – Vol. 9 (10). https://doi.org/10.1371/journal.pone.0109458.

9. Prashanth L. A. et al. Cumulative prospect theory meets reinforcement learning: Prediction and control //International Conference on Machine Learning. – PMLR. - 2016. – pp. 1406-1415.

10. Mavruk T. Analysis of herding behavior in individual investor portfolios using machine learning algorithms //Research in International Business and Finance. – 2022. – Vol. 62. – pp. 1-20. https://doi.org/10.1016/j.ribaf.2022.101740.

11. Choijil E. et al. Thirty years of herd behavior in financial markets: A bibliometric analysis //Research in International Business and Finance. – 2022. – Vol. 59. https://doi.org/10.1016/j.ribaf.2021.101506.

12. Rkein H., Danach K., Rachini A. Decentralized Finance (DeFi) Risk Management Using Explainable AI and Blockchain Transparency //Journal of Computational Analysis & Applications. – 2024. – Vol. 33 (4).

13. Weingärtner T. et al. Deciphering DeFi: A comprehensive analysis and visualization of risks in decentralized finance //Journal of risk and financial management. – 2023. – Vol. 16 (10). – pp. 1-25. https://doi.org/10.3390/jrfm16100454.

14. Coletta A. et al. Towards realistic market simulations: a generative adversarial networks approach //Proceedings of the Second ACM International Conference on AI in Finance. – 2021. – pp. 1-9.

15. Yao Z. et al. Reinforcement learning in agent-based market simulation: Unveiling realistic stylized facts and behavior //2024 International Joint Conference on Neural Networks (IJCNN). – IEEE, 2024. – pp. 1-9.

16. The Seven Sins of Quantitative Investing [Electronic resource] Access mode: https://bookdown.org/palomar/portfoliooptimizationbook/8.2-seven-sins.html (date of request: 29.07.2025).

17. Peng Y. L., Lee W. P. Data selection to avoid overfitting for foreign exchange intraday trading with machine learning //Applied Soft Computing. – 2021. – Vol. 108. https://doi.org/10.1016/j.asoc.2021.107461.

18. Goldblum M. et al. Adversarial attacks on machine learning systems for high-frequency trading //Proceedings of the Second ACM International Conference on AI in Finance. – 2021. – pp. 1-9.

19. Decentralized Finance Market Size and Forecast 2025 to 2034 [Electronic resource] Access mode: https://www.precedenceresearch.com/decentralized-finance-market (date of request: 01.08.2025).