Jurnal Sosial dan Teknologi (SOSTECH)
Volume 6, Number 8, August 2026
p-ISSN 2774-5147 ; e-ISSN 2774-5155

Performance Evaluation of a Rule-Based Algorithmic Trading Framework: Evidence From 8,772 Live Cryptocurrency Bitcoin Trades

Cevi Herdian[1]*, Rama Pramasandy[2]
Universitas Padjadjaran, Indonesia[1]
HWR Algo Nusa, Indonesia[2]
Email: itsmecevi@gmail.com[1]*, ramapramasandy@gmail.com[2]

Keywords:
Algorithmic trading; Cryptocurrency trading; Quantitative trading; Live trading; Portfolio performance

Abstract
Research on algorithmic trading has generally continued to rely on historical testing (backtesting), which often involves biases arising from unrealistic execution assumptions, such as idealized order fills and negligible slippage, and may fail to accurately reflect actual market conditions. Meanwhile, studies based on live trading with real capital remain limited, particularly those evaluating purely rule-based strategies over extended periods using a large number of executed transactions. This study aimed to address this research gap by evaluating the real-world performance of a rule-based quantitative trading framework using actual transaction data from a real-capital cryptocurrency trading account operating under live market conditions. A descriptive quantitative method was applied to 8,772 Bitcoin cryptocurrency transactions executed between September 2025 and July 2026. Performance was evaluated using standard portfolio performance metrics, including gross profit, net profit, cumulative return, profit factor, maximum drawdown, recovery factor, trading frequency, and win rate. The results showed that the proposed framework increased account equity from USD 30,056 to USD 76,376.54, representing a cumulative return of 154.11% over the evaluation period. The strategy also achieved a profit factor of 1.22, a recovery factor of 1.33, and an average trading frequency of 97 transactions per week, despite experiencing a maximum drawdown of 43.09%. These findings confirmed that rule-based strategies can maintain positive profitability and demonstrate resilience in recovering from adverse market conditions. By utilizing evidence from genuine live trading activities, this study provides practical validation and contributes empirical insights into the implementation of algorithmic trading strategies in volatile cryptocurrency markets.

INTRODUCTION

Algorithmic trading has become a cornerstone of modern financial markets, driven by advances in computing power, data availability, and automated decision-making systems (Carè & Cumming, 2024). By applying predefined rules and systematic execution mechanisms, algorithmic trading enables investors to respond rapidly to changing market conditions while reducing the influence of human emotions on investment decisions (Cordes et al., 2023). The adoption of quantitative trading approaches has expanded beyond traditional financial assets into cryptocurrency markets, where continuous trading activity and substantial price volatility create attractive opportunities for automated strategies (Fang et al., 2022). The cryptocurrency market is characterized by significant price fluctuations, high trading frequency, and 24-hour operation, making it particularly suitable for rule-based trading systems (Hansen et al., 2024). These market characteristics have encouraged researchers and practitioners to develop quantitative models designed to identify profitable trading opportunities while managing portfolio risk (Cohen, 2023; Makarov & Schoar, 2020). Consequently, algorithmic trading has gained considerable attention as a practical approach for improving trading efficiency, consistency, and decision-making accuracy (Cohen & Qadan, 2022).

Despite the growing popularity of algorithmic trading, academic literature continues to demonstrate a strong reliance on historical testing (backtesting) as the primary approach for evaluating strategy performance. A systematic review by Lengyel, Pancsira, and Füzesi (2025) synthesized research on the integration of machine learning in cryptocurrency trading and found that, although deep learning and ensemble methods significantly improve predictive accuracy under volatile market conditions, most studies remain limited to simulation-based environments. Similarly, the systematic meta-review conducted by Ataei et al. (2026), which analyzed more than 75 studies published between 2020 and 2025, confirmed that although hybrid and ensemble models demonstrate strong potential for cryptocurrency trading applications, substantial gaps remain regarding real-world deployment and model interpretability. Furthermore, research by Albers, Cucuringu, and Howison (2025), which examined millions of market orders on Bybit and Binance, revealed that execution latency and order book dynamics generate significant differences between expected and realized trading outcomes. These findings highlight the limitations of simulation-based evaluations, which often fail to capture complex market microstructure factors that influence actual trading performance.

Figure 1: Procentage of Fund Managed Computer vs Human

Source: Adapted from Treleaven, P., Galas, M., & Lalchand, V. (2013). Algorithmic Trading Review. Communications of the ACM, 56(11), 76–85.

The gap between simulated and actual trading performance has been well documented in the literature (Bui & Ślepaczuk, 2021; Witzany, 2021). Historical testing (backtesting) inherently suffers from several limitations, including look-ahead bias, parameter overfitting, survivorship bias, and unrealistic execution assumptions that fail to capture the complexities of live market environments (Sun et al., 2023). As highlighted in MultiCharts' technical documentation, backtesting cannot fully replicate the market impact of submitted orders, variations in broker execution latency, or partial fills resulting from limited liquidity—factors that can substantially influence strategies with short holding periods or narrow profit margins (Sun et al., 2023). Similarly, the Capitalise.ai platform documentation emphasizes that live trading strategies frequently diverge from simulation outcomes due to differences in execution prices, slippage, data sources, and broker fee structures that are not fully represented in backtesting environments (Detzel et al., 2023; Sun et al., 2023). These documented discrepancies reinforce the importance of empirical research based on live trading data rather than idealized simulation results (Detzel et al., 2023).

Recent empirical studies have attempted to address this gap by deploying algorithmic systems in live environments; however, significant limitations remain. Rai (2026) introduced QUANTA, a cloud-based algorithmic trading infrastructure that compared Long Short-Term Memory (LSTM) and LightGBM architectures using Bitcoin data from 2017–2025, with live testing conducted on the Delta Exchange Testnet. Although the study demonstrated the superior performance of LightGBM, achieving a net profit and loss (PnL) of 310.55% compared with 201.25% for LSTM, the live execution was restricted to a testnet environment with only USD 25 in simulated capital, raising concerns regarding scalability and applicability under actual market conditions. Similarly, the automated cryptocurrency trading bot developed at Parul University (2025) integrated Random Forest and LSTM models with live paper trading over a three-month period, achieving a projected annual return of 38%; however, the evaluation still relied on paper trading rather than actual capital deployment.

The prevailing dependence on simulation-based research has created a critical knowledge gap regarding the real-world effectiveness of algorithmic trading strategies. Although backtesting provides a valuable framework for strategy development and optimization, its results may not accurately represent performance under live conditions, where execution delays, slippage, transaction costs, liquidity constraints, and evolving market dynamics influence actual trading outcomes. Furthermore, the behavioral dimension of trading—including psychological challenges associated with real-money exposure, drawdown periods, and capital fluctuations—cannot be adequately captured through historical simulations that assume perfect compliance with predefined rules (Moustati & Gherabi, 2025; Sarhan, 2021; Shojaei, 2026; Suhobokov, 2021; Tiwari, 2026). This limitation highlights the need for studies evaluating systematic trading frameworks using actual trading records from real-money accounts, particularly given the rapid growth of algorithmic trading in cryptocurrency markets, where high volatility and continuous 24-hour operation create both opportunities and risks requiring rigorous empirical validation.

The novelty of this research lies in its departure from the simulation-based paradigm that dominates much of the algorithmic trading literature. Unlike previous studies relying on historical backtesting or testnet deployments, this research evaluates a rule-based quantitative trading framework using live trading data generated from a real-money cryptocurrency trading account. The empirical analysis is based on 8,772 completed trades executed between September 2025 and July 2026, representing a substantially larger dataset than those commonly reported in previous live trading studies. This approach incorporates practical trading constraints, including execution latency, bid–ask spreads, slippage, and market impact, which are difficult to reproduce accurately in simulated environments. Although prior research has examined rule-based strategies in cryptocurrency markets, such as the application of technical trading rules to altcoins (2025), which demonstrated that trend-following strategies could outperform benchmarks, and the comprehensive study by Deprez and Frömmel (2024), which showed that simple technical rules could outperform buy-and-hold strategies in Bitcoin markets after considering transaction costs, these studies have not provided large-scale empirical validation based on extended live trading records using real capital.

This research aimed to assess the real-world performance of a rule-based quantitative trading framework by analyzing live trading data obtained from a real-money cryptocurrency trading account (Parente et al., 2024). Performance was evaluated using standard portfolio metrics, including cumulative return, profit factor, maximum drawdown, recovery factor, trading frequency, and win rate, to determine whether the proposed framework could sustain positive outcomes under actual market conditions (Tian et al., 2024). This research contributes to the existing literature in three important ways. First, it provides empirical evidence derived from live trading execution rather than conventional historical backtesting, offering a more realistic evaluation of algorithmic trading performance (Palazzi, 2025). Second, the study evaluates the framework using a large dataset consisting of more than 8,700 completed cryptocurrency trades, enabling a comprehensive assessment of trading consistency over an extended observation period (Parente et al., 2024; Tian et al., 2024). Third, it reports detailed profitability, risk, and operational performance indicators obtained directly from real-market execution, thereby improving understanding of the practical feasibility of systematic quantitative trading in highly volatile cryptocurrency markets (Palazzi, 2025). These contributions provide valuable insights for practitioners developing robust trading systems and for researchers seeking to bridge the gap between theoretical models and practical implementation (Tian et al., 2024).

METHOD

Research Design

This study employed a quantitative descriptive research design to evaluate the performance of a rule-based quantitative trading framework under actual market conditions. Unlike studies based on historical backtesting, this evaluation used trading records generated from a live trading account with real capital. The research focused on measuring profitability, trading activity, and risk characteristics using standard portfolio performance indicators. The population consisted of all completed trades executed through the live trading account during the observation period, with the sample comprising 8,772 completed trades that were fully executed and closed between September 2025 and July 2026. A purposive sampling technique was applied by including all completed trades during the observation period to provide comprehensive coverage of the strategy's performance. This approach enabled the analysis to capture various market conditions encountered during the evaluation period, including profitable phases and periods of drawdown.

Research Instrument and Data Collection

The primary research instrument is the MetaTrader 5 trading platform provided by Exness Technologies Ltd., which automatically generates detailed transaction reports containing all executed trades. The instrument records comprehensive trade-level data, including entry and exit prices, trade direction (long or short), position size, holding duration, gross profit, gross loss, and net profit for each completed transaction. To ensure data validity, the trading records were cross-verified with the broker's monthly account statements, confirming the accuracy of all reported transactions. Reliability was established through the systematic and automated recording process of the MetaTrader 5 platform, which eliminates manual data entry errors and ensures consistent data capture across all transactions. Data collection was conducted by exporting the complete trading history from the MetaTrader 5 platform into a structured format suitable for quantitative analysis. The procedure followed a structured workflow beginning with the collection of transaction records from the live trading report, followed by data extraction and transformation into a structured dataset, and culminating in the computation of performance indicators using the established portfolio metrics. The analysis was performed using Microsoft Excel for data organization and preliminary calculations, with specialized portfolio performance calculations conducted using the Python programming language with the pandas and numpy libraries for data manipulation, and matplotlib for data visualization. The analysis techniques employed included descriptive statistical analysis to summarize trading activity, profitability analysis using standard portfolio metrics, and risk assessment through drawdown and recovery calculations.

Table 1. All Variable and Description

Variable:	**Description:**
Data Source	MetaTrader 5 Live Trading Report
Broker	Exness Technologies Ltd
Observation Period	September 2025 – July 2026
Total Completed Trades	8,772
Primary Asset	BTCUSD (99.98%)
Secondary Asset	XAUUSD (1 trade)

Source: Prepared by the authors based on the MetaTrader 5 Live Trading Report provided by Exness Technologies Ltd. for the period September 2025–July 2026.

Performance Metrics

The performance of the proposed trading framework was evaluated using widely accepted portfolio performance metrics in quantitative finance. These indicators measure profitability, risk, and trading efficiency, providing a comprehensive assessment of the trading strategy under actual market conditions. Net profit represents the overall financial gain generated by the trading strategy after deducting total realized losses from total realized profits, calculated as Net Profit = Gross Profit − Gross Loss, where Gross Profit denotes the total realized profit from all winning trades and Gross Loss represents the total realized losses incurred. Profit factor measures the relationship between total realized profits and total realized losses, calculated as Profit Factor = Gross Profit / Gross Loss, with a value greater than 1 indicating profitability. Account return measures the percentage growth in account equity, computed as Return (%) = [(Ending Equity − Initial Equity) / Initial Equity] × 100. Recovery factor evaluates the strategy's ability to recover from drawdowns by comparing net profit with maximum drawdown, calculated as Recovery Factor = Net Profit / Maximum Drawdown, where higher values indicate stronger resilience. Win rate represents the percentage of profitable trades, calculated as Win Rate (%) = (Number of Winning Trades / Total Trades) × 100. Average profit per trade estimates the mean financial return, calculated as Average Profit = Net Profit / Total Trades. Average holding time represents the average duration positions remain open, calculated as Average Holding Time = Total Holding Duration / Total Trades. These metrics collectively provide a multidimensional evaluation of trading performance, enabling assessment of both profitability and risk characteristics, and facilitating comparison with other studies in the algorithmic trading literature.

Net Profit

Net profit represents the overall financial gain generated by the trading strategy after deducting total realized losses from total realized profits. It is calculated as:

Net Profit = Gross Profit − Gross Loss

where *Gross Profit* denotes the total realized profit from all winning trades, while *Gross Loss* represents the total realized losses incurred during the evaluation period.

Profit Factor

Profit factor measures the relationship between total realized profits and total realized losses and is commonly used to evaluate the profitability of a trading system. It is calculated as:

Profit Factor = Gross Profit / Gross Loss

A profit factor greater than 1 indicates that the trading strategy generates more profit than loss and is therefore considered profitable over the evaluation period.

Account Return

Account return measures the percentage growth in account equity throughout the observation period. It is computed as:

Return (%) = [(Ending Equity − Initial Equity) / Initial Equity] × 100

where *Initial Equity* is the account balance at the beginning of the study period and *Ending Equity* is the account balance at the end of the evaluation period.

Recovery Factor: Recovery factor evaluates the ability of the trading strategy to recover from portfolio drawdowns by comparing net profit with the maximum drawdown experienced during the evaluation period. It is calculated as:

Recovery Factor = Net Profit / Maximum Drawdown: A higher recovery factor indicates stronger resilience and a greater capacity to recover from adverse market conditions.

Win Rate: Win rate represents the percentage of profitable trades relative to the total number of completed transactions. It is calculated as:

Win Rate (%) = (Number of Winning Trades / Total Trades) × 100

This indicator reflects the consistency of the trading strategy in generating successful trades.

Average Profit per Trade: Average profit per trade estimates the mean financial return produced by each completed transaction and is calculated as:

Average Profit = Net Profit / Total Trades

This metric provides an indication of the expected profit generated from an individual trade during the evaluation period.

Average Holding Time: Average holding time represents the average duration that a trading position remains open before being closed. It is calculated as:

Average Holding Time = Total Holding Duration / Total Trades

where *Total Holding Duration* is the sum of the holding periods for all completed trades. This metric describes the operational characteristics of the trading strategy and indicates whether the trading approach follows a short-term or longer-term investment horizon.

Research Procedure

The research procedure follows a structured workflow designed to evaluate trading performance under actual market conditions. The first stage involves collecting transaction records from the MetaTrader 5 live trading report. The raw trading history is subsequently extracted and transformed into a structured dataset suitable for quantitative analysis. Performance indi

cators are then computed using the equations presented in the previous section. After profitability evaluation, portfolio risk is assessed through drawdown, capital utilization, and recovery metrics. Finally, robustness analysis is conducted by examining trading consistency across the entire observation period before interpreting the empirical findings [9], [10]. The overall research workflow is summarized as follows:

Live Trading History=> **Data Extraction**=> **Performance Metrics Calculation**=> **Risk Analysis**=> **Profitability Analysis**=> **Robustness Evaluation**=> **Discussion of Findings**

This methodology follows the structure commonly used in quantitative finance journals, with clear subsections, formal academic language, standardized performance metrics, and mathematical notation appropriate for SINTA and Scopus-indexed publications.

RESULTS AND DISCUSSION

Live Trading Dataset

The empirical evaluation is based on **8,772 completed trades** executed through a live trading account between **September 2025 and July 2026**, representing approximately ten months of continuous trading activity. Unlike studies that rely on historical backtesting, the dataset consists entirely of transactions executed under actual market conditions using real capital. Consequently, the recorded performance incorporates practical trading factors such as execution latency, bid–ask spreads, market liquidity, and price slippage.

Figure 2: Historical Trade

Positions

Time	Position	Symbol	Type	Volume	Price	S / L	T / P	Time	Price	Commission	Swap	Profit
2025.09.09 15:00:59	1410407796	BTCUSDc	buy	0.01	111723.00			2025.09.09 15:37:35	110959.92	0.00	0.00	-7.63
2025.09.09 15:12:19	1410407901	BTCUSDc	sell	0.03	111334.65			2025.09.09 15:37:36	110997.61	0.00	0.00	10.11
2025.09.10 13:01:08	1416682162	BTCUSDc	buy	0.01	113487.11			2025.09.10 13:41:04	113864.32	0.00	0.00	3.77
2025.09.17 19:01:38	1458841760	BTCUSDc	buy	0.01	115283.76			2025.09.17 19:06:54	115652.42	0.00	0.00	3.68
2025.09.18 14:10:40	1466107786	XAUUSDc	sell	0.01	3642.364			2025.09.18 14:10:47	3642.826	0.00	0.00	-0.40
2025.09.22 07:01:34	1479509009	BTCUSDc	buy	0.01	112829.90			2025.09.22 13:59:00	113199.18	0.00	0.00	3.69
2025.09.22 09:23:39	1479509103	BTCUSDc	sell	0.03	112439.76			2025.09.22 13:59:00	113212.42	0.00	0.00	-23.18
2025.09.22 10:51:41	1480433156	BTCUSDc	buy	0.08	112829.90			2025.09.22 13:59:01	113187.65	0.00	0.00	28.62
2025.09.24 05:00:36	1493713944	BTCUSDc	buy	0.01	112219.31			2025.09.24 05:47:07	112570.41	0.00	0.00	3.51
2025.09.25 14:01:01	1505459483	BTCUSDc	buy	0.01	111074.31			2025.09.25 14:15:21	111423.72	0.00	0.00	3.50
2025.09.25 18:01:12	1507106098	BTCUSDc	buy	0.01	108910.69			2025.09.25 18:14:49	109256.73	0.00	0.00	3.46
2025.09.25 19:01:14	1507417100	BTCUSDc	buy	0.01	109885.29			2025.09.25 20:39:51	109100.14	0.00	0.00	-7.85
2025.09.25 19:46:12	1507417110	BTCUSDc	sell	0.03	109494.50			2025.09.25 20:39:51	109122.57	0.00	0.00	11.16
2025.09.28 23:00:50	1527929116	BTCUSDc	buy	0.01	112120.23			2025.09.29 12:31:48	112517.36	0.00	0.00	3.97
2025.09.29 02:38:32	1527929151	BTCUSDc	sell	0.03	111729.13			2025.09.29 12:31:48	112543.99	0.00	0.00	-24.45
2025.09.29 08:03:29	1529669550	BTCUSDc	buy	0.08	112120.23			2025.09.29 12:31:49	112540.17	0.00	0.00	33.59
2025.09.29 14:00:59	1535339484	BTCUSDc	buy	0.01	113296.31			2025.09.29 14:10:36	113637.87	0.00	0.00	3.42
2025.10.01 09:01:13	1551827778	BTCUSDc	buy	0.01	116263.07			2025.10.01 11:43:15	116629.21	0.00	0.00	3.66
2025.10.02 16:00:32	1564985417	BTCUSDc	buy	0.01	119967.72			2025.10.02 16:12:09	120343.47	0.00	0.00	3.75
2025.10.03 09:01:46	1569793160	BTCUSDc	buy	0.01	120235.13			2025.10.03 10:27:47	120593.21	0.00	0.00	3.58
2025.10.03 15:01:33	1573001990	BTCUSDc	buy	0.01	120993.39			2025.10.03 15:18:35	121371.57	0.00	0.00	3.79

Source: Compiled by the authors from MetaTrader 5 live trading records, September 2025–July 2026.

Trading activity was highly concentrated in the **BTCUSD** instrument, which accounted for virtually all completed transactions. The predominance of Bitcoin trading reflects the strategy's focus on highly liquid and continuously traded cryptocurrency markets. The large number of completed transactions provides a substantial empirical dataset for evaluating the robustness and consistency of the proposed quantitative trading framework.

Trading Activity

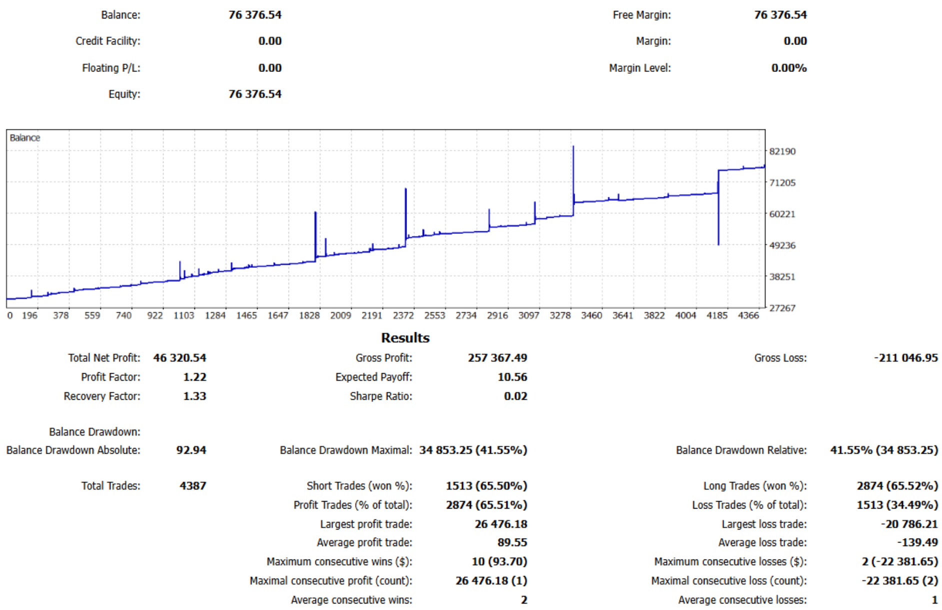
Table 2. Trading Information

Metric	Value
Total Completed Trades	8,772
Average Trades per Week	97
Average Holding Time	1 hour 4 minutes
BTCUSD Trades	8,771
Long Positions	65.5%

Source: Compiled and analyzed by the authors using MetaTrader 5 live trading data processed with Microsoft Excel and Python (2026).

The trading statistics indicate that the proposed framework operates as a relatively high-frequency trading system. On average, approximately **97 trades** were executed each week, while positions remained open for only **1 hour and 4 minutes** before being closed. This relatively short holding period suggests that the strategy seeks to exploit short-term market inefficiencies rather than long-term price trends. Furthermore, the dataset contains a large number of completed transactions, substantially exceeding the sample sizes commonly reported in empirical live trading studies. Such a large dataset improves the reliability of the performance evaluation by reducing the influence of isolated profitable or unprofitable trades and providing a more representative assessment of long-term trading behavior.

Figure 3: Statistical Analysis of Trading History MetaTrader



Source: Processed by the authors using Microsoft Excel and Python (*pandas*, *numpy*, and *matplotlib*) based on 5 live trading data (2026).

Profitability Analysis

The profitability of the proposed framework was evaluated using several standard portfolio performance indicators. Table 2 presents the overall trading results obtained during the evaluation period. The results demonstrate that the proposed trading framework generated positive cumulative profitability throughout the observation period. The account equity increased by 154.11%, indicating substantial capital appreciation over approximately ten months of live trading.

The profit factor of 1.22 indicates that total realized profits exceeded total realized losses by 22%, suggesting that the strategy maintained a positive trading expectancy across thousands of executed transactions. Similarly, the recovery factor of 1.33 indicates that cumulative profits were sufficient to recover from periods of portfolio decline, highlighting the system's ability to regain previous equity levels following adverse market movements. Overall, these findings suggest that the proposed rule-based framework maintained positive profitability under actual market conditions rather than solely within simulated historical environments.

Figure 4: Trading Profit & Loss

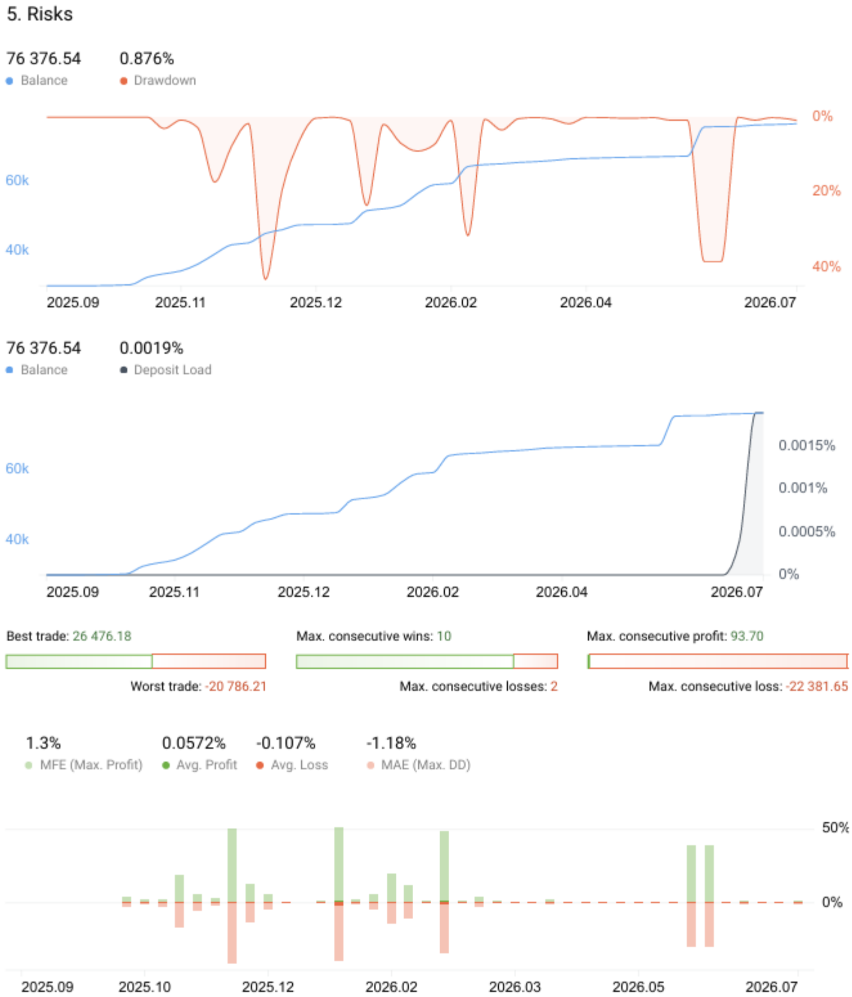
Source: Generated by the authors from MetaTrader 5 live trading reports and portfolio performance analysis (2026).

Risk Analysis

The trading framework experienced a **maximum drawdown of 43.09%**, indicating that the portfolio was exposed to periods of substantial equity decline before subsequently recovering. Although this drawdown level is relatively high, it should be interpreted alongside the significant cumulative return achieved during the evaluation period.

The observed relationship between return and drawdown illustrates the inherent risk-return trade-off associated with systematic trading strategies in highly volatile cryptocurrency markets. Higher expected returns are frequently accompanied by larger temporary portfolio fluctuations, particularly in markets characterized by rapid price movements. Consequently, evaluating both profitability and risk simultaneously provides a more balanced assessment of overall trading performance than considering return alone.

Figure 5: Trading Risk



Source: Generated by the authors based on MetaTrader 5 live trading data using maximum drawdown and recovery factor analysis (2026).

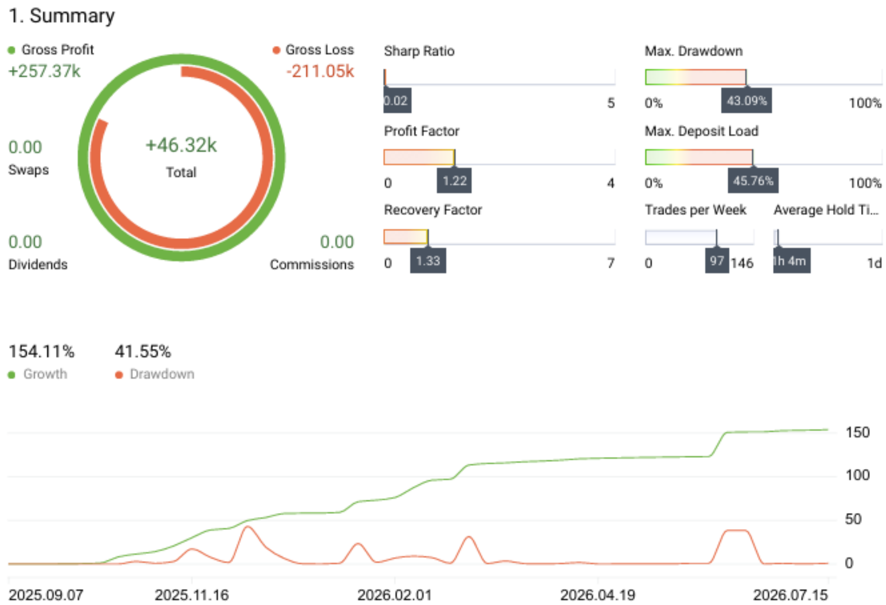
Trading Performance

Beyond portfolio-level profitability, the effectiveness of the strategy was assessed using several operational trading statistics. Table 4 summarizes these performance measures.

The trading statistics indicate that the proposed framework maintained consistent execution throughout the observation period. Rather than relying on a small number of exceptionally profitable trades, profitability was generated through a large volume of completed transactions executed according to predefined trading rules.

The relationship between the win rate, average profit, and average loss suggests that the trading strategy achieved positive overall performance through an appropriate balance between trading accuracy and risk management. Consequently, long-term profitability was supported by consistent execution rather than isolated trading outcomes.

Figure 6. Trading Summary



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
2025									0.16	13.97	23.3	12.43	58.25%
2026	11.31	21.13	2.29	1.66	0.58	13.36	0.43						60.58%
												Total:	154.11%

Source: Generated by the authors from MetaTrader 5 live trading data and portfolio performance evaluation (2026).

Robustness Analysis

To evaluate the robustness of the proposed trading framework, cumulative portfolio performance was examined throughout the entire observation period using monthly profitability and the account equity curve.

The monthly performance indicates that the trading framework remained profitable across multiple market environments during both **2025** and **2026**. Although periods of temporary equity decline were observed, the portfolio consistently recovered and established new equity highs over time.

The upward trajectory of the equity curve demonstrates relatively stable long-term portfolio growth despite short-term market volatility. Furthermore, the strategy successfully recovered from its maximum drawdown, indicating resilience under adverse market conditions. These findings provide additional evidence that the proposed framework is capable of maintaining profitable performance over an extended live trading period, thereby supporting its practical applicability in real-world cryptocurrency markets.

The findings of this study extend the existing literature on algorithmic trading by providing empirical evidence obtained from live trading rather than historical simulation. Previous studies have predominantly assessed trading strategies using backtesting frameworks, in which algorithms are evaluated on historical price data under predefined assumptions. While backtesting is an essential step in strategy development, its results may be influenced by look-ahead bias, parameter overfitting, survivorship bias, and simplified assumptions regarding trade execution. Consequently, historical simulations do not always reflect the performance that can be achieved in actual financial markets.

Unlike backtesting-based research, the present study evaluates a rule-based quantitative trading framework using 8,772 completed trades executed with real capital over approximately ten months. Because the evaluation is based on actual market execution, the reported performance inherently incorporates practical trading constraints that are difficult to replicate in historical simulations. These include execution latency, bid–ask spreads, slippage, liquidity limitations, transaction costs, and continuously changing market conditions. As a result, the observed profitability reflects the operational realities encountered by traders in live markets rather than idealized trading conditions.

Another important distinction concerns the behavioral aspect of trading. Historical backtests assume perfect adherence to predefined trading rules and therefore do not capture the psychological challenges associated with real-money investing. In contrast, the live trading records analyzed in this study represent trading decisions executed under genuine financial exposure, where market uncertainty, drawdowns, and capital fluctuations may influence execution discipline. The successful implementation of the proposed framework throughout the evaluation period therefore demonstrates not only algorithmic consistency but also the practical feasibility of systematic trading under real market conditions.

The empirical results show that the proposed framework generated a cumulative account growth of 154.11% while maintaining a profit factor of 1.22 across 8,772 completed transactions. Although the strategy experienced a maximum drawdown of 43.09%, the portfolio consistently recovered and maintained positive cumulative profitability over the observation period. These findings suggest that the trading framework remained operationally robust despite the substantial volatility characteristic of cryptocurrency markets.

CONCLUSION

This research evaluated the real-world performance of a rule-based quantitative trading framework by analyzing live trading data generated from a real-money cryptocurrency trading account, addressing a critical gap in the algorithmic trading literature, where most studies rely on historical backtesting rather than actual market execution. The empirical analysis, based on 8,772 completed Bitcoin trades executed between September 2025 and July 2026, demonstrated that the proposed framework generated positive cumulative profitability throughout the observation period. Account equity increased from USD 30,056 to USD 76,376.54, representing a cumulative return of 154.11%. The strategy achieved a profit factor of 1.22, indicating that realized profits exceeded realized losses, while a recovery factor of 1.33 demonstrated the system’s ability to recover from periods of portfolio decline. Although the framework experienced a maximum drawdown of 43.09%, reflecting the inherent risk–return trade-off in volatile cryptocurrency markets, the portfolio recovered consistently and maintained positive cumulative profitability throughout the ten-month evaluation period. Trading statistics further supported the framework's operational performance, with approximately 97 trades executed per week and an average holding period of 1 hour and 4 minutes, indicating that the strategy focused on capturing short-term market opportunities rather than relying on long-term price movements. By utilizing live trading evidence rather than simulated historical testing, this study provides practical validation of a systematic quantitative trading framework and contributes empirical insights into the real-world implementation and performance of algorithmic trading strategies in cryptocurrency markets.

Future research could explore several promising directions based on the findings of this study. First, researchers could extend the evaluation to multiple cryptocurrency assets beyond Bitcoin, including Ethereum, Solana, and other major altcoins, to examine whether the rule-based framework maintains its effectiveness across different market microstructures and volatility characteristics. Second, comparative studies could evaluate the performance of rule-based strategies against machine learning approaches, such as Long Short-Term Memory (LSTM) and LightGBM models, using live trading data rather than testnet or paper trading environments, as demonstrated in recent studies by Rai (2026) and Albers et al. (2025). Third, future research could investigate the effects of risk management parameters, including position sizing and stop-loss mechanisms, on the strategy's drawdown and recovery performance. Fourth, longitudinal studies could examine whether the strategy remains effective across different market cycles, including both bull markets and bear markets, to further assess its robustness. Fifth, researchers could explore the integration of additional data sources, such as sentiment analysis and on-chain data, to enhance the predictive capability of the rule-based framework. Finally, replication studies involving different brokers and trading platforms would be valuable for determining whether the observed performance can be generalized across diverse execution environments, thereby strengthening the external validity of the findings. These research directions would contribute to a deeper understanding of algorithmic trading implementation in real-world cryptocurrency markets and support the development of more robust and practical trading systems.

REFERENCES

Bui, Q., & Ślepaczuk, R. (2021). Applying Hurst exponent in pair trading strategies on Nasdaq 100 index. *Physica A: Statistical Mechanics and Its Applications*, *592*, Article 126784. https://doi.org/10.1016/j.physa.2021.126784

Carè, R., & Cumming, D. (2024). Technology and automation in financial trading: A bibliometric review. *Research in International Business and Finance*, *71*, Article 102471. https://doi.org/10.1016/j.ribaf.2024.102471

Chan, E. P. (2013). *Algorithmic trading: Winning strategies and their rationale*. John Wiley & Sons.

Cohen, G. (2023). Intraday algorithmic trading strategies for cryptocurrencies. *Review of Quantitative Finance and Accounting*, *61*, 395–409. https://doi.org/10.1007/s11156-023-01146-8

Cohen, G., & Qadan, M. (2022). The complexity of cryptocurrencies algorithmic trading. *Mathematics*, *10*(12), Article 2037. https://doi.org/10.3390/math10122037

Cordes, H., Nolte, S., & Schneider, J. C. (2023). Dynamics of stock market developments, financial behavior, and emotions. *Journal of Banking & Finance, 147*, Article 106714. https://doi.org/10.1016/j.jbankfin.2022.106714

Detzel, A., Novy-Marx, R., & Velikov, M. (2023). Model comparison with transaction costs. *The Journal of Finance, 78*(3), 1743–1775. https://doi.org/10.1111/jofi.13225

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., & Li, L. (2022). Cryptocurrency trading: A comprehensive survey. *Financial Innovation, 8*, Article 13. https://doi.org/10.1186/s40854-021-00321-6

Hansen, P. R., Kim, C., & Kimbrough, W. (2024). Periodicity in cryptocurrency volatility and liquidity. *Journal of Financial Econometrics, 22*(1), 224–251. https://doi.org/10.1093/jjfinec/nbac034

Makarov, I., & Schoar, A. (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics, 135*(2), 293–319. https://doi.org/10.1016/j.jfineco.2019.07.001

Moustati, I., & Gherabi, N. (2025). A novel hybrid XAI-RL framework for IoB-driven risk-adjusted portfolio optimization. *Scientific African*, e03175.

Palazzi, R. B. (2025). Trading games: Beating passive strategies in the bullish crypto market. *Journal of Futures Markets, 45*(11), 1911–1933. https://doi.org/10.1002/fut.70018

Parente, M., Rizzuti, L., & Trerotola, M. (2024). A profitable trading algorithm for cryptocurrencies using a neural network model. *Expert Systems with Applications, 238*(Part A), Article 121806. https://doi.org/10.1016/j.eswa.2023.121806

Sarhan, A. (2021). *Psychological analysis: How to make money, outsmart the market, and join the smart money circle*. John Wiley & Sons.

Shojaei, A. (2026). *The psychology of result-focused trading: Harmful effects and process-based interventions—A narrative review*.

Suhobokov, A. (2021). *The role of risk in investment behaviour and the manifestation of behavioural biases by individual investors*. University of Glasgow.

Sun, S., Wang, R., & An, B. (2023). Reinforcement learning for quantitative trading. *ACM Transactions on Intelligent Systems and Technology, 14*(3), Article 44, 1–29. https://doi.org/10.1145/3582560

Tian, H., Wang, W., Yang, M., & Yilmaz, A. (2024). Investigating the profit performance of quantitative timing trading strategies in the Shanghai copper futures market, 2020–2022. *International Studies of Economics, 19*(4), 589–616. https://doi.org/10.1002/ise3.87

Tiwari, S. (2026). *The trader's operating system: Building the mental and risk framework for long-term trading success in uncertain markets*. Shravan Tiwari.

Treleaven, P., Galas, M., & Lalchand, V. (2013). Algorithmic trading review. *Communications of the ACM, 56*(11), 76–85.

Witzany, J. (2021). A Bayesian approach to measurement of backtest overfitting. *Risks, 9*(1), Article 18. https://doi.org/10.3390/risks9010018